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The Power of The Press

An Experimental Investigation into News-driven Inflation Expectations

by

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This study investigates the extent to which news affects individuals' inflation expectations through an innovative experimental design. The results show that news treatment significantly affects inflation expectations, with varying degrees of impact observed across different inflation regimes. Furthermore, the study reports differences between sexes, with women reacting more strongly to news treatment than men. These findings hold important implications for central banks and policymakers as they emphasize the significance of considering the effects of news coverage on shaping inflation expectations. Moreover, the identified heterogeneities between sexes offer valuable insights for policymakers seeking to tailor their strategies and interventions to specific subsets of the population based on their inflation expectations.

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1 Introduction

In the wake of the Covid-19 crisis, several countries, including Sweden, have witnessed historically high inflation rates. This increase affects everyone, from households and firms to governments. This surge in inflation has widespread impacts, extending from everyday households and business entities, all the way to governments. A wealth of studies has demonstrated that inflation rates are driven by inflation expectations an element that is incorporated into many macroeconomic models. The critical question, then, is: what shapes these expectations? Survey evidence suggests that households base their understanding of current price levels on personal shopping experiences, along with information sourced from both social and traditional media, including newspapers (Kumar et al. 2015; Cavallo et al. 2017; D'Acunto et al. 2021). This study focuses particularly on this latter aspect. Studies show that media coverage of inflation impacts inflation expectations (Bollinger, 2023). In their study, Larsen, Thorsrud, and Zhulanova (2021) established the crucial role that newspapers play in shaping expectation formation processes. As such, it becomes essential to further explore the extent to which news media influences inflation expectations—a focal point of investigation in this thesis.

Moreover, standard macroeconomic models assume that individuals form rational and homogeneous inflation expectations, however, empirical studies show that these expectations are generally biased upwards and vary considerably across demographic groups (Cavallo et al. 2017). This deviation has important implications for monetary policy and the predictive accuracy of macroeconomic theory. The lack of empirical evidence on inflation expectation formation has contributed to disagreements among monetary policymakers (Burke and Manz, 2014). As a result, policymakers and academics alike are increasingly interested in studying how individuals form inflation expectations. In particular, Bernanke (2007) highlights the potential discrepancy between actual inflation expectations and those implied by macroeconomic models and urges further study into the factors affecting the level of inflation expectations.

Taken these together, in today's high inflation environment, it is particularly important to study individuals' inflation expectations. Determining the extent to which news influences these expectations is not only an intriguing academic topic but is also a crucial issue for policy development. Of particular interest is whether agents react differently to environmental shifts in scenarios of rising versus falling inflation. This understanding is instrumental in selecting the most effective policy design. Therefore, I aim to answer the following research question:

" To what extent does news affect inflation expectations in increasing and decreasing inflationary settings?"

1.1 Aim

This study aims to investigate the extent to which inflation expectations are affected from news with a particular focus on determining whether changes in the inflation regime (increasing or decreasing) impact this relationship. In pursuit of this aim, the study conducts an inflation forecasting experiment.

The study further entails three subsidiary objectives:

1. To formulate relevant sub questions drawing on the inflation expectations literature.

2. To gather data and build a novel quantitative dataset based on the experiment, thereby facilitating the empirical investigation of the research questions in varied inflation contexts.

3. Investigate the research questions through data collected from the experiment.

1.2 Outline of the Thesis

The paper continues with a literature review on inflation expectations in the next section, followed by a discussion of the research question in the third section. The fourth section explains why I chose to use experiments, and the fifth discusses the methodology, detailing both data analysis and experimental design. In the sixth section, I report the findings. The seventh section provides a discussion of these results, and the eighth section concludes the study.

2 Literature review

In economics, "expectations” refers to the views and predictions that individuals maintain about key future variables such as prices, taxes, incomes, sales, among others . The earliest documented reference to economic expectations can be traced back to Ancient Greece. In his work, Politics, Aristotle discussed Thales of Miletus (636-546 BC), who achieved significant profits by accurately predicting a future olive harvest. This example underscores the reason why expectations are so pivotal in economics: they significantly influence the present-day decisions and choices of households and firms. As such, expectations of the future shape the current overall level of economic activity (Mikołajek-Gocejna, 2014).

Inflation expectations are a critical concept in economics and are considered a key determinant of actual inflation. They refer to the rate at which people—consumers, firms, investors—anticipate prices will rise in the future. These expectations can significantly influence economic behavior and decision-making, playing a vital role in areas such as wage negotiations, price setting, investment decisions, and savings rates (Assenza et al. 2014). The economic literature pertaining to expectations is vast. Accordingly, this paper will concentrate predominantly on the aspect of inflation expectations. Furthermore, it is imperative to maintain the focus and coherence of the discourse, hence, extraneous concepts that do not contribute to the forthcoming analysis will not be introduced.

2.1 Theories of Inflation Expectations

The primary focus of theories of inflation expectations have mainly been on how public and private information influences expectations. However, there is no consensus over the theoretical explanations of how inflation expectations are formed (Mankiw and Reis, 2018). It is important to note that the majority of theories explaining inflation expectations are not solely focused on inflation. Instead, these theories primarily model the general process of expectation formation.

There exist divergent perspectives among economists regarding the formation of inflation expectations. The Adaptive Expectations Hypothesis (AEH), one of the earlier theories developed to explain expectations, suggests that individuals' expectations are largely based on past experiences and trends (Cagan, 1956). For instance, if inflation has been consistently high in the past, individuals would expect it to remain high in the future. Conversely, if inflation has been low, a similar low rate would be anticipated. AEH offered a systematic way to capture how expectations could adjust over time in response to observed changes in economic variables. (Mikołajek-Gocejna, 2014). AEH, however, is not without its limitations. It suggests that individuals react passively to changes in economic conditions, merely updating their expectations based on past data. This can lead to systematic errors in expectation formation, as it suggests that individuals do not learn from their past mistakes. Additionally, AEH theory does not take into consideration situations in which people quickly modify their expectations in reaction to new information (Mikołajek-Gocejna, 2014).

In response to these concerns, the Rational Expectations Hypothesis (REH), which became the prevalent approach to modeling expectation formation following the foundational work by Muth (1961) and Lucas (1972) was proposed. REH presumes that agents utilize all accessible information and can, on average, generate unbiased forecasts of future economic variables, that is, without consistent errors. When all agents form rational expectations, the economy will arrive at the rational expectations equilibrium (REE). REH has been widely adopted due to its simplicity, although it has received criticism for its assumptions about agents' understanding of the economy's law of motion and their computational capabilities (Mikołajek-Gocejna , 2014).

These criticisms have led to alternative theories. One of these theories suggests agents exhibit bounded rationality, a theory tracing its roots back to Simon (1957). The theory posits that individuals' decision-making processes are not always perfectly rational due to the cognitive limitations of the agents and the finite amount of time available to make decisions. The crux of this approach lies in the observation that real market participants' expectation formation doesn't seem to align with the rationality model. For example, during the US housing market boom, investors expected an implausibly high growth rate in housing prices, a finding highlighted by Shiller (1990) and Case et al. (2012).

Another theory is the sticky-information model, which postulates that people do not constantly update their expectations as new information becomes available. Instead, the process of gathering and processing new information involves costs (time, effort, resources), which leads to people updating their information intermittently. This results in what is termed as "information stickiness” (Mankiw and Reis 2002). In the context of inflation, the sticky-information model suggests that individuals and firms slowly adjust their inflation expectations to changes in actual inflation, rather than instantaneously, potentially updating their expectations periodically, such as when they receive a payment or encounter a news report about the economy.

Following the discussion on the sticky information models, another noteworthy approach to understanding expectation formation involves Noisy Information Models. This line of thinking suggests that economic agents continuously update their information, however, the signals individuals receive about various economic variables are imperfect, or "noisy" (Woodford, 2002). Such signals are typically a blend of the actual value of the variable in question and some random error (Kose et. al, 2019). To illustrate, consider the varying figures for the current rate of inflation provided by different sources. In such a situation, individuals are compelled to estimate the true rate based on these slightly divergent figures; thus, within this framework, these noisy signals shape individuals' expectations, leading to potential errors in the formation of expectations.

Similarly, rational inattention models, pioneered by economist Christopher Sims, are based on the idea that collecting and processing information is costly. Therefore, individuals optimally choose to pay attention to only a subset of available information, a behavior known as "rational inattention." In this framework, individuals may not always respond to changes in economic variables immediately or fully, not because they are unaware of these changes, but because they have rationally chosen not to pay attention to them. Rational inattention can lead to inertia in expectation formation and decision-making, and it provides a rationale for phenomena like delayed adjustment to changes in economic policy (Sims, 2003).

2.2 Empirical Research on Inflation Expectations

The empirical research on inflation expectations primarily falls into two distinct categories. The first category builds on existing data, analyzing field evidence such as surveys to derive insights. The second category involves the elicitation of expectations, often utilizing various experimental methods. In the former category, the core objective is to test various theories of inflation expectation formation (Malmendier & Nagel, 2016; Carrol, 2003). For example, Coibion and Gorodnichenko (2015) employ models of information frictions to explain the underreaction to new information when forming inflation expectations. Bordalo et al. (2020) undertake an examination of the rational expectations theorem. Based on survey data, they find that while the aggregate inflation forecasts typically exhibit an underreaction relative to the predictions of the rational expectations theory, the inflation forecasts made by individual respondents conversely show a tendency towards overreaction.

Forsell and Kenny (2002) show that consumer expectations converge to rational expectation, albeit an intermediate manifestation of rationality. Their results demonstrate that the expectations gathered from surveys act as estimators of forthcoming price fluctuations, albeit not entirely at times and integrate, a variety of macroeconomic data. Furthermore, even though there have been constant gap between consumers' expectations and Rational Expectations, they show that consumers rationally modify their expectations over time in order to "eliminate " any systematic errors. On the other hand, employing international surveys, Coibion and Gorodnichenko (2015) provide evidence of state-dependence in inflation formation. This suggests the adoption of diverse forecasting behaviors, such as adaptive, sticky information, and rational expectations, in varying circumstances. Their research also identifies information rigidities among individuals, leading to departures from rational expectations.

Prior research utilizing survey data has identified notable heterogeneity in inflation perceptions and expectations, linked to demographic and socioeconomic characteristics. Bryan and Venkatu (2001), in their survey of Ohio consumers, found that women reported higher rates of both past and anticipated future inflation compared to men. This result remained consistent even when adjusting for other demographic variables such as age, education, income, race, and marital status. Leung (2009), on the other hand, reported that individuals with lower educational attainment tended to form higher inflation expectations.Furthermore, Malmendier and Nagel (2016) find that age-related heterogeneity remains statistically significant even after controlling for the age-specificity of the consumption basket.

Research analyzing consumer survey data from various countries such as the United States (Bruine de Bruin et al. 2010, Pfajfar and Santoro 2008, Souleles 2004), New Zealand (Leung 2009), England (Blanchflower and MacCoille 2009), and Ireland (Duffy and Lunn 2009), consistently indicates that people from households with lower incomes generally have a higher perception of inflation and expect it to rise more than those from households with higher incomes. However, an analysis of consumer surveys in South Africa (Kershoff, 2002) presents a contrasting result, with lower-income individuals perceiving and expecting less inflation than their higher-income counterparts. Moreover, households' future inflation expectations are found to be strongly influenced by their beliefs about past inflation (Jonung 1981; Malmendier and Nagel 2016). One of the theories has been proposed to explain this is the impact of "sticky information" on households' inflation expectations. As put forward by Carroll (2003), households' expectations are subject to "sticky information", which refers to individuals not instantly updating their beliefs or expectations in response to new information, often due to cognitive constraints or costs associated with acquiring and processing new data. Another is that household surveys may not distinguish between "informed" and "uninformed" consumers, assigning equal weight to both. Uninformed consumers, likely to overemphasize frequently purchased goods such as food or goods with highly visible price changes like gasoline, may consequently push their inflation expectations upward in response to price increases of these items (Coibion and Gorodnichenko, 2015; Coibion, Gorodnichenko, and Kamdar 2018; Sousa and Yetman 2016).

Financial literacy (including numeracy and economics) is also found to drive heterogeneity in inflation expectations. In a survey study, Bruine de Bruin et al. (2010) show that individuals with lower financial literacy are more inclined to base their inflation expectations on their own personal financial status as opposed to aggregate indicators like CPI inflation. Positive forecasting errors were also more prevalent in less literate individuals. Comparable results are presented in works such as those by Calvet et al. (2009), Duca and Kumar (2014), Lusardi and Mitchell (2014), Lipshits et al. (2019), and Rumler and Valderrama (2020).

2.2.1 Experimental Literature on Inflation Expectations

In the experimental literature on inflation expectations, there are three types of experimental design:

1. Learning to Forecast Experiments (LtFE): In this experimental setup, subjects act as professional forecasters within a stimulated economy. Subjects' main task is to forecast an economic variable, e.g, inflation rate. The LtFE is pioneered by Marimon and Sunder (1993), where authors explore the formation of inflation expectations in a laboratory setting, challenging the validity of the Rational Expectations Hypothesis. Another prominent application of this design is by Hommes et al. (2005, 2008) on a speculative asset market. In these experiments, subjects play the role of investment advisor of pension funds and submit an asset price forecast.

2. Learning to Optimize Experiments (LtOE): This category involves experiments in which participants directly submit their economic decisions (mostly quantities regarding production, trading and savings). Notably, this approach does not necessitate elicitation of participants' forecasts. One of the notable studies following this design is Bao et al. (2012), where authors investigate whether Rational Expectations hold in a cobweb economy, which is a type of economic model where current decisions, such as production quantities, are based on past price. Other studies that use this design are Arifovic (1996) (exchange rates) and Noussair et. al (2007) (production).

3. Survey Experiments: This design entails the administration of survey questions to participants within a controlled environment, which allows for the careful collection and analysis of their responses. Primarily, this body of literature has centered its attention on expectations concerning inflation (Armantier et al. 2015, 2016; Binder and Rodrigue, 2018; Cavallo et al., 2017; Coibion et al., 2018) and house prices (Armona et al., 2019).

There is considerable experimental literature that tests the applicability of various theoretical models including, but not limited to rational expectations, adaptive expectations, sticky and noisy information models. For instance, Pfajfar and Zakelj (2014) reported that subjects demonstrated a variety of behaviors when formulating inflation expectations within a New Keynesian sticky-price model, lending credence to multiple theoretical models. This heterogeneity was observed in both within and between subjects. Adam (2007) presented experimental evidence indicating subjects' propensity towards a "restricted perceptions equilibrium" in forecasting inflation, implying their forecasts rely solely on historical inflation and neglect other pertinent macroeconomic data. Finally, Armantier et al. (2015) elicited inflation expectations from an experimental survey and scrutinized their behavior in an investment experiment, where payoffs were influenced by future inflation. They concluded that a substantial proportion of subjects opted for investments aligning with their inflation expectations, and that individuals demonstrating behavior seemingly inconsistent with their expectations generally scored lower in assessments of financial literacy and numeracy.

The findings from experimental literature echo those of survey data-based research. For example, it has been observed that women consistently hold higher inflation expectations than men (D'Acunto et al. 2021). Younger individuals, on the other hand, generally have lower inflation expectations than their older counterparts (Malmendier and Nagel 2016). Additionally, consumers of lower socioeconomic standing — a categorization based on both income and education levels — are often found to have higher inflation expectations (Das et al. 2020). Studies also reveal that individuals with lower cognitive abilities, even after adjusting for education and income levels, tend to anticipate higher inflation rates than others (D'Acunto et al. 2019, 2022). Lastly, minority consumers are generally found to hold higher inflation expectations compared to their native counterparts. Further, Burke and Manz (2014) found that individuals with higher economic and financial literacy had lower inflation forecasting errors. It's important to note that this study generated its own inflation data based on a statistical model, which was then used as a benchmark to compare average inflation forecasting errors.

2.2.2 Information Provision Experiments

More recently, there is a growing literature on information provision experiments that investigates how the provision of information affects the inflation expectations of individuals. For example, Armantier et al. (2016), in a survey experiment, shows that individuals do update their expectations based on new information, but the degree of adjustment depends on the individual's personal experiences and beliefs. This emphasizes the importance of individual-level factors in determining how people form and adjust their expectations about inflation.

Also in a survey experiment, Binder and Rodrigue (2018) scrutinize how consumers' long-term inflation expectations react to information related to the Federal Reserve's inflation target and historical inflation data. On a general scale, it was observed that participants adjusted their forecasts towards the 2% target in response to either type of information. Though the treatments resulted in reduced forecast uncertainty and heterogeneity, these aspects still remained significant. Given that the information in the treatments is publicly accessible, the findings align with models of imperfect information where individuals do not completely or consistently update their information sets, or do not integrate all accessible information into their expectations. The reactions to the treatments were also found to fluctuate based on participants' prior knowledge and demographic attributes.

Moreover, Cavallo et al. (2017), in another survey experiment, find that information rigidities are central in the formation of inflation expectations. They report that cognitive limitations emerge as a potential source of information frictions: even when statistical information about inflation is readily accessible, individuals persist in giving considerable weight to inaccurate information sources, such as their recollections of price changes for supermarket products they have purchased.

2.3 The Media and Inflation Expectations

The media occupies a critical position in shaping inflation expectations, given that households derive their knowledge of current price levels not only from personal shopping experiences but also from social media, television news, and newspapers (Blinder & Krueger 2004; Kumar et al. 2015; Cavallo, Cruces, and Perez-Truglia 2017; D'Acunto et al. 2021). Consequently, the media has the potential to guide how consumers adjust their inflation expectations (Doms & Morin, 2004), mirroring its influence in other domains such as voting behavior, as illustrated by studies like DellaVigna and Kaplan (2007), Hetherington (1996). Viewed through an economic lens, it is a logical choice for consumers to use news reports as a cost-efficient method for acquiring economic information. Sims (2003) argues that the manner in which the media delivers economic news affects how individuals react to it. Therefore, the style and substance of media reporting play a crucial role in the formation of expectations.

Numerous empirical studies have examined how the media affects people's expectations of inflation, including those by Carroll (2003), Pfajfar and Santoro (2013), Lamla and Lein (2014), and Lamla and Maag (2012). For newspapers, Larsen, Thorsrud, and Zhulanova (2021) find that news media coverage plays an important role in the expectation formation process. They find that news media coverage is a statistically significant predictor of households' inflation expectations In addition, during periods of intense media coverage, such as during economic downturns, households are observed to adjust their expectations more frequently (Carroll 2003; Doms & Morin 2004).

According to Soroka (2006), news of a decrease in inflation is positive for households, whereas news of an increase in inflation is bad. However, it is crucial to differentiate between the sentiment of the text and the perceived sentiment of the information. News that reports increasing inflation can be worded neutrally but information wise it can be perceived negatively, a perspective also supported by Bollieger (2023) in a contemporary study. It's worth noting that media coverage can exhibit a tendency towards more upwardly biased inflation news. This inclination is shown by both Hamilton (2004) and Soroka (2006), who have identified a prevalence of upwardly biased news on inflation. Consequently, it's plausible that the media could be contributing to bias within this particular transmission channel. In fact, Pfajfar and Santoro (2013) finds that upward biased news on inflation (higher prices) increases the inflation forecast of survey respondents, whereas downward biased news exert no statistically significant influence on the inflation forecasts. Furthermore, they argue that households may not be optimally utilizing the information they receive, as they consistently diverge from the average expectations of professional forecasters, showing no signs of suitable adjustments in their predictions. This could be understood as a possible consequence of media-transmitted news potentially containing a judgemental assessment of the experts opinions, hence causing a distortion in consumers' expectations. As a result, media reports might exhibit bias, disseminating "distorted" expectations.

In a study investigating the impact of media on inflation expectations in Germany, Lamla and Lein (2014) find that survey respondents' reaction of inflation expectations to news delivered by media reports depends on both the quantity and the content of news. Echoing the aforementioned argument, the authors argue that upward or downward framed news are not inherently sentimental. Therefore, they make a distinction between sentimentality and upward/downward biased news. In particular, they find that news that is framed neutrally about rising inflation can increase forecast accuracy. In a parallel investigation on survey data, Dräger (2015) explores the influence of media on inflation expectations in Sweden. The author identifies an asymmetrical impact of news about inflation either increasing or decreasing. The study's findings reveal that news about inflation rising has no bearing on inflation expectations, while news about falling inflation, surprisingly, increases inflation expectations.

2.4 Contribution and Connection to the Literature

This thesis broadly relates to three strands of literature. First, a literature that studies the role of information for inflation expectations (Cavallo et al. 2017; Armantier et al. 2016). Second, by analyzing the function of media in the expectation creation process, it directly relates the work of Doms and Morin (2004), Pfajfar and Santoro (2013), Lamla and Lein (2014) and Dräger and Lamla (2017). Last, from a methodological perspective, the thesis is connected to the recent and fast-growing information provision literature that links textual information to both economic and financial outcomes (see Haaland, Roth & Wohlfart, 2021 for a review).

The primary contribution of this paper lies in its examination of varying inflation scenarios, namely, upward and downward trends. As highlighted in the literature review, Cavallo et al. (2017) found that individuals react differently to information when forming inflation expectations in high versus low inflation contexts. This aspect becomes particularly relevant in light of the recent surge in inflation observed in Sweden, reinforcing the pertinence of the study. This paper also contributes to the literature on the media's (news) role in shaping inflation expectations. To the best of my knowledge, this is the first study to examine this relationship within an experimental framework, incorporating varying inflation trends.

This paper diverges from the aforementioned studies in two significant ways. Firstly, my focus is exclusively on the degree to which inflation expectations of individuals are influenced by upward and downward biased news. Importantly, my emphasis is not on sentiment but on content; these represent two distinct elements of news as highlighted in the literature review. Secondly, on a different but related note, I am not interested in investigating whether subjects' inflations converge to or diverge from a particular model, or if they learn about a particular model in the lab, both of which studied extensively as presented in the literature review. Instead, my interest lies in the variation in inflation expectations and its observable determinants in different inflation settings.

As such, my experimental design differs in several key respects from that of previous experiments which elicited inflation expectations. First, in order to prevent subjects from learning about the model during the course of the exercises, I never informed them of the “correct” inflation forecast in a particular exercise. Second, in my setting, future inflation outcomes are determined by a statistical model and not influenced by subjects' expectations. This design feature is consistent with the notion that, in the real world, people are likely to act as if their individual expectations do not affect future inflation (Burke & Manz, 2014). Another distinctive aspect of this study, setting it apart from other information provision experiments, is the inclusion of a historical plot of inflation rates in forecasting exercises. This feature serves to mitigate the variability arising from individual differences in recollection of past inflation rates or personal experiences with inflation, thereby enhancing the robustness of the comparisons across subjects and treatments.

3 Research Questions

Given the focus of this study and the key research sub questions identified the following questions are proposed:

My main research question is:

1. *To what extent does news affect inflation expectations in increasing and decreasing inflationary settings?*

As presented in the literature review, studies show that there are high levels of heterogeneity in inflation expectations due to observable demographic and personal characteristics.

Therefore, I also ask these sub questions:

1. *Do inflation expectations exhibit heterogeneity across various demographic characteristics both before and after the treatment?*

2. *Does a higher economic and financial literacy score among individuals reduce their susceptibility to the influence of news on their inflation expectations?*

These research questions guide the subsequent stages of experimental design and analysis in this study. The answers derived will add to the existing body of knowledge on the role of news demographic characteristics and economic and financial literacy in shaping inflation expectations.

4 Why an Experiment?

This investigation implements an experimental methodology, the specifics of which will be elaborated in the following section. Prior to delving into the particulars of the design, it is pertinent to articulate the rationale behind favoring an experimental approach over survey-based research.

As presented in the previous section, the existing literature on inflation expectations are based on two principal research approaches: surveys and experiments. Polling consumers about their perceptions and expectations of inflation in real-time, survey data provides valuable insights. Panel surveys, in particular, are instrumental in observing how expectations react to changes in realized inflation and other macroeconomic conditions, while controlling for individual characteristics (Assenza et. al. 2014). However, survey methods do come with their own set of limitations.

Firstly, survey participants may lack sufficient incentives to make an accurate forecast, unlike in real-world scenarios where a poor forecast could lead to economic repercussions. This could mean that inflation forecasts in surveys might not be as meticulously considered as they would be in real-life situations, although the prominence of incentives linked to inflation forecasts is a matter of debate and fluctuates with inflation itself (Assenza et. al. 2014). Secondly, and more significantly, researchers are not privy to the information subjects have access to and the process of data generation in surveys (Afrouzi et. al. 2021). In this context, this would mean that the researcher does not know what kind of information survey respondents are subject to.

The experiment I conducted addresses these limitations in several ways. Firstly, participants were compensated based on the precision of their forecasts, providing them with an incentive to consider their predictions thoughtfully. This also allowed for the convergence of incentives, meaning everyone is playing the same "game" for the same (similar) reasons. Secondly, as a researcher, I was in full control of the data generation and could dictate the information accessible to the subjects within the experimental setting. Lastly, the participants' behavior in the experiment unveiled aspects of the expectation-formation process that are not easily discernible through survey methodologies. While the experiment's design inevitably set certain boundaries on this process, it is my assertion that the design brings to light significant facets of the subjects' beliefs regarding the forces behind inflation. This, in turn, provides insights into how they might forecast inflation in real-world situations.

5 Methodology

5.1 Experimental Design

The present study utilizes a between-subjects design, an experimental design in which subjects are divided into separate control and treatment groups, with each group exposed to a different condition of the study. In contrast to a within-subjects design, where each subject experiences all conditions and serves as their own control, a between-subjects design allows researchers to compare the effects of different conditions across different groups. The key difference between within-subject and between-subject design is in how the independent variable is manipulated. In within-subject design, the independent variable is manipulated within each participant, whereas in between-subject design, the independent variable is manipulated between groups of participants (Charness et al. 2012).

There are several reasons for employing a between-subjects design in this study. Foremost, such designs are known to minimize learning effects across different conditions. This is especially crucial for the objectives of this study, where the aim is to understand the role of news in the presence of data (Budiu, 2018). Secondly, between-subjects studies typically have shorter sessions than within-subject ones. This is particularly important considering that participants were not compensated for their involvement in the experiment. The fact that the experiment took an average of 15 minutes made it more feasible to recruit participants. However, it is important to acknowledge that between-subjects designs are not without limitations. Such a design necessitates a larger participant pool and it does not minimize random noise to the extent that a within-subject design does. As a result, true differences between conditions might remain undetected or be obscured by random noise (Charness et al. 2011). Note that subjects in the treatment group answer 4 forecasting exercises, therefore one might argue that there are learning effects. However, also note that the study does not provide any feedback and the experiment's nature does not facilitate learning.

5.1.1 Experiment Procedure

In this section, the experimental framework for the empirical analysis in this paper is described. This structure draws inspiration from several previous studies (Burke & Manz, 2014; Afrouzi et al. 2021; Roos & Schmidt 2012), while incorporating novel elements specifically designed to explore diverse inflation scenarios. The experimental interface was built using Otree, which is an open-source platform for laboratory, online, and field experiments (Chen,Schonger & Wickens, 2016). See Appendix A for full instructions.

The experiment is composed of five sections, as follows:

1. A demographic questionnaire where participants answer questions about age, sex, education level, etc.
2. An initial brief questionnaire focusing on past and future inflation trends in Sweden,
3. For the control questions, there are 4 inflation forecasting exercises only based on a history plot
4. For the treatment, there are the same 4 inflation forecasting exercises accompanied by a neutrally framed news paragraph for each exercise.
5. A set of 16 multiple-choice questions that measure economic and financial literacy.

Each phase of the experiment are systematically executed, accompanied by instructions at every juncture. Prior to the forecasting exercises, participants had the chance to familiarize themselves with a user-friendly interface, designed to assess their comprehension of the guidelines. Additionally, they are briefed on the data generation process.

5.1.2 Questions

Demographic Questions and Opening Questions

Upon introductions, the demographics questionnaire asks questions on the respondent's and mother's age, sex, country of birth, current employment status, and educational history. Along with these questions, participants are questioned on how often they thought about inflation in the last 3 months, how frequently they saw/read/heard about inflation in the last 3 months, how they typically learn about inflation as well as who is doing grocery shopping in their household. These questions are added to provide deeper comparability between control and treatment groups as well as the broader Swedish population.

Questions about Past and Future Sweden Inflation

In this segment, participants were requested to complete a multiple-choice questionnaire, aimed at eliciting their understanding of inflation. Subsequently, participants received feedback as to the correct definition of inflation, which stated that it denotes the rate at which the general price level of goods and services within an economy increases. Then, participants were asked to identify the variable and period they would be forecasting. After this, they received the correct answers. This is particularly important to ensure the robustness of the analysis.

Thereafter, the participants were presented with examples of inflation rates expressed as annual percentage changes in the price level, encompassing both positive and negative values. Participants were then required to proffer an approximation of the mean inflation rate that prevailed within Sweden during the previous year, in addition to providing a projection of inflation over the following year. These questions were posed to generate additional data points, facilitating a more robust comparison between the control and treatment groups and ensuring the quality of the data collected remains high. Note that both control and treatment groups partook in this questionnaire.

Inflation Forecasting Exercises

After answering the questions from the previous section, subjects were randomly assigned to control or treatment. In the control phase, participants are asked to forecast based on a history plot. In the treatment, participants are tasked with forecasting inflation based on upward and downward biased short news articles. Each forecasting exercise required participants to predict inflation rates for one year in the future, using percentages with up to two decimal places. The instructions made it clear that the situations presented are hypothetical, and participants are not expected to forecast real-world inflation. Nonetheless, participants were informed that the data they would be working with behaves as though it comes from a real economy. They were told, correctly, that the situations they faced were generated by a model that was built upon historical Swedish data for 192 years. From the simulated time series, I selected snapshots (5 periods) of contemporaneous data pertaining to CPI inflation. I made sure that different trends had similar slopes to make comparisons across exercises easier. Note that I use yearly CPI, which is calculated as the change in the CPI in a specific month compared to the same month in the previous year (Sveriges Riksbank, 2023). The primary reason for choosing yearly CPI is due to its prominence in the news reports.

Participants neither received feedback on their forecasts, nor did their expectations influence the ultimate inflation outcomes. This was due to two key reasons. First, it was to prevent participants from learning about the accuracy of their forecasts, and consequently about the model, during the course of the experiment. Second, it mirrored real-life circumstances where individuals often behave as though their personal expectations have no impact on future inflation (Assenza et al. 2014).

Producing News Paragraph (Upwards vs Downwards Biased)

In order to generate news paragraphs imbued with either upward or downward framing concerning future inflation trends, I utilized ChatGPT- 4, which is a type of advanced Large Language Model developed by OpenAI. It uses AI technology to produce human-like text and is designed to engage in human-like conversations, provide personalized responses, and understand the context of any conversation. ChatGPT-4 can perform a wide range of tasks such as answering questions, summarizing text, generating lines of code, creating and song lyrics, It can handle over 25,000 words of text, allowing for use cases like long-form content creation, extended conversations, and document search and analysis. ChatGPT-4 is considered one of the most advanced and precise in text creation (Wodecki, 2022).

Note that exact prompt was:

(1) Write a neutrally worded hypothetical news article of approximately 100 words that communicates an expected rise in inflation for the coming year for Sweden.

(2) Write a neutrally worded hypothetical news article of approximately 100 words that communicates an expected fall in inflation for the coming year for Sweden.

Also, note that none of the news articles included any numerical data to avoid anchoring of inflation forecasts. I, then, did qualitative robustness checks to ensure neutrality and quality through textual analysis. The starting point for identifying positive and negative words is the Harvard IV Psychosocial Dictionary, a general lexicon of written English that flags words with positive or negative connotations. The positive words include terms such as "boom," "improve," "success" and "proper," while negative words include "adverse," "disrupt," "fragile," and "unforeseen." Although the psycho-social dictionary may categorize certain terms such as "demean" or "hedge" as having negative connotations in common usage, their semantic valence may not necessarily carry over to the context of economic forecasting. As such, the inclusion of such terms in a lexicon geared towards economic outlook may not be justified. Therefore, I followed Sharpe, Sinha and Hollrah (2022)'s list, which culled a customized lexicon of 231 positive words and 102 negative words from these lists.

Economic Literacy Questions

The questionnaire on economic and financial literacy consists of 16 multiple-choice questions. These cover topics such as knowledge of monetary policy, fundamental principles of personal finance, and numeracy. Included in these questions is the previously mentioned definition of inflation, which is asked prior to the forecasting exercises. The purpose of repeating this question is to gauge whether participants are paying close attention to the experiment. As a result, 98% of respondents answered this question correctly on their second attempt, indicating a high level of attentiveness. The questions include those from Burke and Manz (2014) and van Rooij, Lusardi, and Alessie (2011), as well as subtle variations of them. Subjects are instructed to select the one accurate response from a list of four options that followed each question. Please see the appendix for all of the questions.

5.1.3 Sample Size

Determining the necessary sample size for a study is guided by the calculations of statistical power and effect size. The literature suggests a power value of 0.8 for information provision experiments (Haaland, Roth, & Wohlfart, 2021), which is commonly used in statistical power calculations. As for the effect size, Cohen's d is utilized as the measurement tool, which is derived from the standardized difference between the means of two groups as originally proposed by Cohen in 1988. Effect sizes of 0.2, 0.5, and 0.8 are generally interpreted as small, medium, and large, respectively.

To my knowledge, there aren't any similar studies that could be referenced to determine the treatment effects. As a result, I rely on the outcomes of my pilot experiments to aid in determining these effects. Therefore, I anticipate the treatment effect to be closer to a medium effect, around 0.53. Consequently, this results in a total minimum required sample size of 50.I use G*Power[1], which is widely used statistical software to calculate the sample size (Faul et al. 2009).

[1] I applied the following settings : For 'Test Family', I selected 'F tests'. Under 'Statistical Test', I chose 'ANOVA: Fixed effects, omnibus, one-way'. For the 'Type of Power Analysis', I opted for 'A priori: Compute required sample size - given α, power, and effect size'."

5.1.4 Practicalities

I conducted 13 separate sessions of the experiment, following three pilot experiments. The pilots took place online on the 17th, 19th, and 21st of April 2023, and consisted of nine subjects, all students at Lund University. During the test run, I understood that several subjects had difficulty understanding some terms. Following this, I improved the instructions for the simulated economy forecasting exercises and added an instructions quiz. The main experiments took place a week after the pilot, between the 1st and 18th of May 2023. These were conducted in a hybrid format and consisted of a total of 72 subjects, including both Lund University students and non-students from the Venture Lab - Lund University Incubator. In the following analysis, I refer only to data generated by these main experiments.

5.2 Data Generating Process (DGP)

To generate data for inflation, I use a model calibrated with 192 years of historical yearly CPI data from Sweden (1831-2022) using the Autoregressive Integrated Moving Average (ARIMA) process. The ARIMA model is commonly used in forecasting inflation. A notable aspect of the ARIMA methodology is its performance superiority in short-term forecasts, despite lacking a direct theoretical foundation in economics. This has often resulted in it surpassing econometric models that are grounded in economic theory. This phenomenon has been documented in several studies, such as those by Stockton and Glassman (1987), Nadal-De Simone (2000) and Saz (2011). In recent decades, numerous scholars have undertaken case studies to evaluate the stochastic dynamics of inflation data by employing ARIMA models across various countries. Some of the countries studied are Albania, Bahrain, Finland, Ghana, Iran, Ireland, Morocco, Nigeria, Romania, Senegal, Slovenia, Sweden and Turkey (Jafarian-Namin et al. 2021)

It is important to note that this paper's focus isn't on identifying the "optimal" model for predicting inflation. Instead, it strives to select an appropriate model for simulating inflation, ensuring that individuals participating in the experiments encounter realistic and recognizable inflation values. Therefore, I will intentionally omit certain diagnostic checking processes to maintain the paper's focus and avoid overcomplicating the scope of the research.

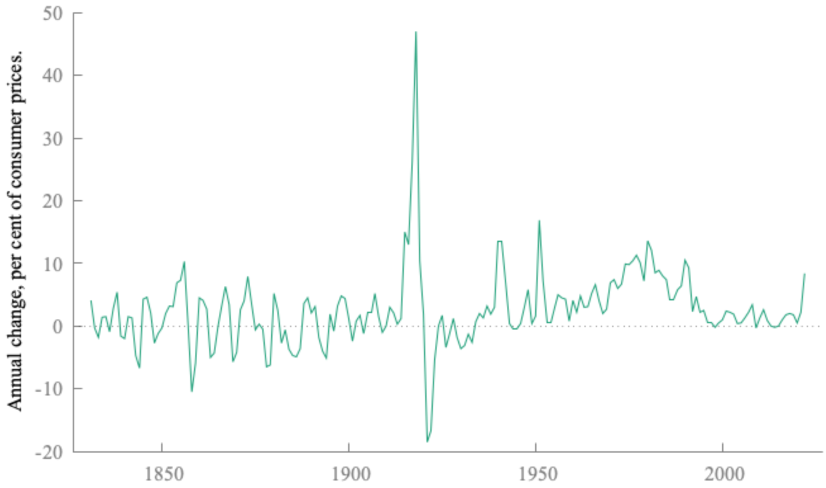

Figure 1. Inflation in Sweden 1830–2022

5.2.1 ARIMA Model

The ARIMA (Autoregressive Integrated Moving Average) model is a type of time series model that utilizes time-ordered data to gain insight into the structure of the underlying process and to predict future values. The notation for an ARIMA model is typically written as ARIMA(p,d,q), where 'p' is the order of the Autoregressive part, 'd' is the number of differencing required to make the time series stationary and q is the order of the Moving Average part. For instance, an ARIMA (1,2,1) model implies the existence of one autoregressive variable and one moving average variable, with the time series requiring two rounds of integration (or differencing) to achieve stationarity. If the series is already stationary and doesn't necessitate any integration, the model simplifies to an ARMA(p,q) model (Hyndman & Athanasopoulos, 2018).

To formally represent ARIMA models, the Autoregressive (AR) and Moving Average (MA) operators must first be defined individually as follows:

$$\phi(B) = 1 - \phi_1 B - \cdots - \phi_i B^i - \cdots - \phi_p B^p, \quad \phi_p \neq 0 \tag{1}$$

$$\theta(B) = 1 - \theta_1 B - \cdots - \theta_j B^j - \cdots - \theta_q B^q, \quad \theta_q \neq 0 \tag{2}$$

In this context, ϕ_i represents the Autoregressive term of the $\boldsymbol{i}$th order, θ_j denotes the Moving Average term of the $\boldsymbol{j}$th order, and B signifies the backshift operator, which is a notation used to describe the relationship between past observations and future observations in a time series Hyndman and Athanasopoulos (2018). Typically, an ARIMA(p,d,q) model is characterized by a combination of p Autoregressive elements, d integrated elements, and q Moving Average elements, as described below:

$$\phi(B)(1-B)^d X_t = C + \theta(B)a_t \tag{3}$$

In this expression, X_t is homogeneously non-stationary if $W_t = (1-B)^d$, which represents the differencing step in ARIMA is stationary. The constant term C is represented by $\mu(1-\phi_1-\phi_2-\cdots-\phi_p)$, where μ is the process mean. Furthermore, a_t is a normally and independently distributed random error with a mean of 0 and a variance of σ_a^2 .

5.2.2 Model Specification

The process of Data Generation with the ARIMA model follows a conventional sequence of Box and Jenkins Methodology which encompasses a series of techniques used to identify and estimate time series models, specifically within the ARIMA model class. This involves gathering and inspecting data, assessing the time-series for stationarity, identifying, and estimating the model, conducting diagnostic checks, generating forecasts, and evaluating their accuracy (Meyler, Kenny & Quinn, 1998).

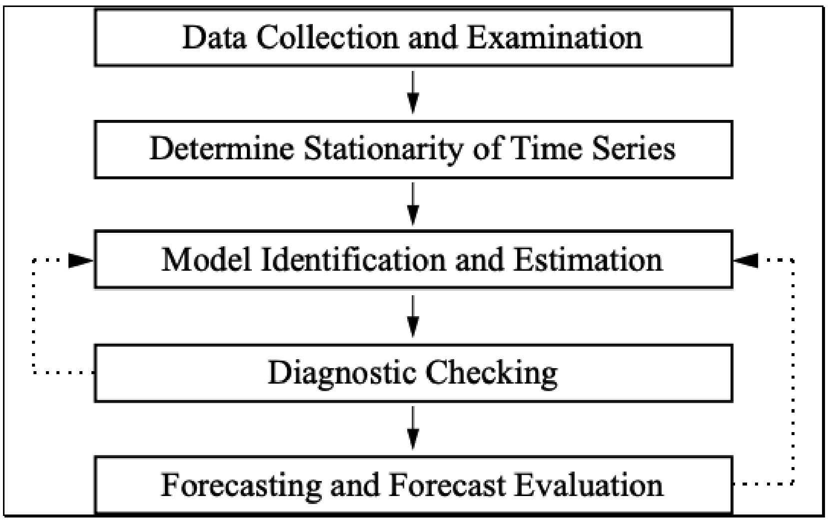

Figure 2 Box and Jenkins Methodology (Source: Meyler, Kenny & Quinn. 1998)

Data Collection and Examination

For univariate time series forecasting, it's important to have a sufficient amount of data. Ideally, there should be at least 50 observations (Hyndman & Athanasopoulos, 2018). When the available data is insufficient, the application of methods such as Box-Jenkins or objective penalty function can encounter difficulties. The data set at hand consists of 192 data points (1831-2022).

Stationarity Testing

To begin the model specification process, first, the stationarity of the series should be checked using the Augmented Dickey-Fuller (ADF) test. Before embarking on the task of identifying an appropriate ARIMA model, it's critical to ensure that the time series being analyzed is stationary (Meyler, Kenny & Quinn. 1998). Stationarity implies that the stochastic characteristics of the time series, including its moments (mean, variance, covariance), remain constant over time.

Stationarity is essential for ARIMA models due to its impact on predictability, model specification, stability, and interpretability. A stationary time series makes the series more predictable and manageable for the ARIMA model. Stationarity underpins the assumptions of constant mean and variance, necessary for model stability and reliability. Lastly, stationarity aids in the consistent interpretation of model parameters, crucial for understanding the model's output. Thus, ensuring stationarity is fundamental for effective ARIMA modeling (Box et al. 2015).

To test the stationarity, Augmented Dickey Fuller (ADF) test should be executed. The ADF test is a type of unit root test that tests the null hypothesis that a series possesses a unit root and is therefore non-stationary. The formula for the Augmented Dickey Fuller unit root test (ADF) is as follows:

$$\Delta y_t = \beta_0 + (\alpha - 1) y_{t-1} + \Sigma_{i=1}^{p} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{4}$$

Where, β_0 represents a constant, $(\alpha - 1)$ stands for the coefficient being tested for the unit root, and $\alpha_i \Delta y_{t-i}$ symbolizes the additional lags that are summed up.

In simpler terms, a unit root refers to a situation where a time series behaves like a random walk, with shocks having a lasting effect. This is due to the nature of the underlying mathematical equations, where the 'roots' of these equations fall within a certain range, causing the series to be non-stationary. If the series doesn't have a unit root, it's considered stationary because the mathematical conditions for randomness aren't met. A characteristic equation, linked with the time lags in the data, is involved in this process. If there's exactly one unit root, subtracting the previous value from the current value (first order differencing) will make the series stationary. If there are exactly two unit roots, doing this process twice (second order differencing) will lead to stationarity. For finding the most simplified model with the ideal lag length, a testing-down approach as detailed in Cottrell and Lucchetti (2009) is employed. I set the maximum lag at 6, which aligns with literature recommendations (Schwert, 1989; Harris, 1992; Taylor, 2000). The ADF test results suggested that the time series was stationary, having a p-value below 0.05. This was an indication that differencing would not be needed to make the series stationary.

Model Identification

In the process of identifying the model for the stationary time series, two graphical instruments are employed - the autocorrelation function (ACF) and the partial autocorrelation function (PACF). These tools aid in unveiling the correlative structure inherent in the data (Meyler, Kenny & Quinn. 1998). The ACF measures the correlation for each set of ordered pairs (Z_t, Z_{t+k}) across varying time lags. The PACF, on the other hand, quantifies the direct correlation between ordered pairs, disregarding the impact of observations at other intervening time lags $(Z_t, Z_{t+1}, \cdots, Z_{t+k-1})$ (Jafarian-Namin et al. 2020).

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots should be evaluated in conjunction to determine the type of process. For an Autoregressive (AR) process, it is anticipated that the ACF plot will decline gradually, and concurrently, the PACF plot will exhibit a sharp fall after p significant lags. Conversely, for a Moving Average (MA) process, we anticipate the ACF plot to show a sudden decline after a specific q number of lags, whereas the PACF plot should depict a slow, geometric decrease. Alternatively, if both the ACF and PACF plots reveal a slow decrease, the Autoregressive Moving Average (ARMA) process should be employed for modeling (Hyndman & Athanasopoulos, 2018).

In my scenario, both the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) display a pronounced drop following the initial lag (see Appendix). Additionally, both demonstrate significant correlations at the second lag. Based on these preliminary analyses, I proposed an ARIMA(1,0,1) model as a starting point for modeling the inflation data. The order parameters were chosen as follows: the differencing order was set to 0, due to the stationarity of the original series, while the autoregressive and moving average orders were set to 1, given that the ACF and PACF plots.

Model Comparisons

The suggested ARIMA model specification should serve as an initial framework, which can be honed through model fitting diagnostics and validation using hold-out data. The process of model selection in time series analysis necessitates a thoughtful equilibrium between statistical evaluation, rooted in diagnostic tests and plots, and practical factors such as model complexity and comprehensibility. Consequently, the following steps would involve fitting this ARIMA model to the data, scrutinizing the residuals for any persistent patterns or correlations, and evaluating its performance against other possible models based on statistical standards like the Akaike Information Criterion (AIC) (Box et al. 2015).

The application of information criteria during the model identification stage involves estimating all pertinent ARIMA models that fit the data at different parameter lengths. The top five models for each criterion are then selected to proceed to the forecasting phase, where the best model will be chosen based on its forecasting performance.

Table 1 - Comparison of Ranking by Criterion

	Model	AIC
Rank 1	(2,0,1)	1140.312
Rank 2	(1,0,1)	1141.408

Rank 3	(1,0,2)	1142.153
Rank 4	(1,0,0)	1143.200
Rank 5	(2,0,0)	1148.307

Even though the model with the (2,0,0) configuration demonstrates the highest performance, this paper will instead employ the (1,0,1) model. This decision is guided by the insights derived from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Furthermore, the Akaike Information Criterion (AIC) performance between the two models is nearly equivalent, further justifying the choice of the (1,0,1) model.

5.3 Data Analysis

The data analysis starts with the descriptive analysis of the data. This is done by comparing the differences in means between control and treatment groups for each exercise and plotting the distributions. Next, to ascertain whether the differences between means are statistically significant, Mann-Whitney U test is performed. In contrast to student's t test, Mann-Withney U test is a nonparametric test that does not require the assumption of normality for the variable at hand (inflation forecasts)[2]. The reason for employing this test was because the data did not indicate normality which was tested through Kolmogorov-Smirnov and Shapiro-Wilk tests. See Appendix for values of each exercise.

The Kolmogorov-Smirnov test is a non-parametric test that compares the cumulative distribution function for a variable with a specified distribution (in this case, a normal distribution). If the p-value (Sig.) is less than 0.05, this implies that the data deviates from a normal distribution. Shapiro- Wil test, on the other hand, is also a commonly used method to test for normality. However, this test is more suitable for small sample sizes. Similar to the former test, p-value lower than 0.05 indicates deviation from a normal distribution.

[2] It's important to clarify that this type of normality is different from the normality found in regression analysis. While this normality refers to the data at hand, the normality in regression specifically pertains to the residuals, which are the differences between the observed and predicted values.

In an attempt to gauge the effect of treatment (news) on inflation forecasts, a regression analysis is performed. It is important to note that the experimental design employed at this study resembles that of a within subject due to participants answering 6 questions. Therefore, it can be argued that mixed models are more suitable. However, although participants are forecasting inflation in each exercise, each exercise possesses differences in terms of the history plot and news article accompanying it. Therefore, each exercise is analyzed individually through OLS regressions. Similar applications could also be found in the literature (Cavallo et al. 2017).

In the following sections, more technical descriptions of the models are presented.

5.3.1 Mann-Whitney U-test

The Mann-Whitney U test is a non-parametric statistical test that is used to determine if there are statistically significant differences between two independent groups when the dependent variable is either ordinal or continuous. The Mann-Whitney U-test does not require any assumptions about the distribution of the data, in contrast to the student's t-test. However, the test requires a number of assumptions to hold. First, the observations in the two groups being compared should be independent from each other. That is, an observation in one group should not affect the observations in the other group. This implies that there needs to be random sampling, meaning each member of the population has an equal chance of being selected, and the selection of one member does not affect the selection of another. Second, the dependent variable (inflation forecasts) should be measured at least at the ordinal (which means the data should be rank ordered) or continuous form. Third, each subject (or item) should belong to one and only one group. This implies that there needs to be control and treatment groups. And, lastly, this is not a strict assumption, but the Mann-Whitney U test has greater power if the shapes of the distributions of the two groups are similar. Differences in group distributions can affect the interpretation of the test results (Glenn, 2023).

The Mann-Whitney U-test tests the following. There are two independent random variables Xc and Xt, where c denotes control group and t treatment group. The hypotheses of the test are:

1. Null Hypothesis (H0): The two population distributions are identical, so that there is a 50% probability that an observation from a value randomly selected from one population exceeds an observation randomly selected from the other population.
2. Alternative Hypothesis (H1): The two population distributions are not identical.

The procedure is as follows:

1. Combine all data from both groups and rank them together from smallest to largest. Tied ranks may be handled by assigning to each group the average of the ranks they would have received if they were not tied.
2. Calculate the sum of the ranks for the observations from each group separately. Let's denote these as R_1 and R_2.
3. The test statistic U for each group can be calculated as follows:

$$U_1 = n_1 n_2 + n_1(n_1 + 1)/2 \ - R_1 \tag{5}$$

$$U_2 = n_1 n_2 + n_2(n_2 + 1)/2 \ - R_2 \tag{6}$$

Note that, n_1 and n_2 represent the number of observations in each group.The smaller of U_1 and U_2 is used as the test statistic.The test statistic is then compared to a critical value from the U distribution (which is a known set of values) or the p-value is computed for the test statistic to decide whether to reject the null hypothesis. If the U statistic is less than the critical value or the p-value is less than the significance level (typically 0.05), we reject the null hypothesis and conclude that the two groups differ significantly.

5.3.2 Ordinary Least Squares Regression

Within the framework of the study, the utilization of Ordinary Least Squares (OLS) regression presents an advantageous strategy for assessing the magnitude and direction of differences between our designated groups. In the context of OLS regression, the coefficients assigned to the independent variables serve as indicators of the expected alteration in the dependent variable for each unit change in the corresponding independent variable. This change is considered with the caveat that all other variables remain constant.

As a specific example, if we examine 'treatment' as an independent variable within the model (coding it as '0' and '1' to denote two respective groups), the coefficient derived for 'treatment' will illustrate the anticipated difference in the dependent variable that is attributable to the two groups. The inherent value of OLS lies in its ability to provide a detailed understanding of both the magnitude and direction of differences between groups. However, as with any statistical method, there are inherent assumptions that need to be satisfied for the results to be deemed valid. For OLS, these assumptions include linearity, homoscedasticity (equal variances), and the normality of residuals (Frost, 2023). If these assumptions are violated, the integrity of the results could be compromised. Therefore, prior to performing OLS regression, I have tested for these assumptions[3]. See Appendix E for results.

The model specification is presented in equation (7). $Forecast$ denotes the dependent variable, which is the *inflation forecast*. Note that B_1 identifies the average change in forecasts of agents in the treatment group relative to the average change in the control group. α is the constant term, and *i* denotes an individual. Treatment is a dummy for being in the *treatment* group. X_i is a vector of individual specific controls, which are age, sex, employment status, country of birth, level of education and economic literacy.

$$Forecast_i = a + B_1 Treatment_i + B_2 X_i + error_i \tag{7}$$

[3] The test results suggest that only one condition, 'homoscedasticity', wasn't met, and this was only the case for some exercises. So, to handle this, I used 'regressions with robust standard errors'.

5.4 Sample Statistics

Table 2 Summary Sample Statistics

	Control		Treatment	
Variable	Mean	SD	Mean	SD
Sex	0.56	0.50	0.51	0.51
Age	2.03	0.94	1.94	1.01
Nationality	0.86	0.35	0.85	0.35
Country of birth	0.78	0.42	0.76	0.42
Employment	0.58	0.50	0.56	0.51
Level of education	3.44	0.80	3.33	0.83
Prior inflation expectation	7.96%	2.97	8.32%	3.57
Future inflation expectation	8.52%	4.85	8.62%	4.64
Economic literacy	54%	13.76	51%	13.86
Grocery	0.85	0.35	0.88	0.32
Thinking frequency	1.61	0.73	1.72	1.00
Hearing frequency	1.97	1.13	1.69	0.82
N	36		36	

In this section, the sample statistics are presented, and the quality of the data is discussed. The variables are presented in detail in Table 2, which confirms that the different treatment groups are comparable along all major observable characteristics, implying that there is strong evidence of successful random sampling. Moreover, Table D.1 in Appendix D shows a comparison of the control and treatment groups to the broader Swedish population. The results indicate that the sample is similar to the broader Swedish population, which ensures data quality. However, it should be noted that the sample is relatively younger and has a lower employment rate compared to the overall Swedish population. Additionally, the subjects in the sample have lower inflation expectations for the past 12 months and slightly higher inflation expectations for the next 12 months. This difference can be attributed, at least in part, to the fact that population statistics for inflation expectations are based on data from March 2023.

6 Results

6.1 Forecasting Exercise-1 (Upward trend accompanied by upward biased news)

Table 3 Mean inflation forecasts, Forecasting Exercise-1

Treatment	Sex	Mean	Std. Deviation
0	0	5.69	3.183
	1	5.02	4.635
	Total	5.32	4.015
1	0	9.52	2.927
	1	6.13	1.698
	Total	7.92	2.947

Before delving into the analysis below, it's crucial to recall that Forecasting Exercise-1 demonstrated an upward trend, which was accompanied by upwardly biased news. The results of Mann-Whitney U Test show a statistically significant difference between the control and treatment groups (See Table E.1 in Appendix E). A more detailed analysis revealed that the control group (treatment = 0) indicated a mean forecast value of 5.3. In contrast, the treatment group showed a mean forecast value of 7.9. This represents a change of 2.6 percentage points in the forecasts, suggesting that upwardly biased news articles increased the forecasts by this amount.

Differences in inflation forecasts related to gender were observed. Within the control group, women (Sex = 0) had a slightly higher mean forecast value (Mean = 5.6) than men (Sex = 1) (Mean = 5.02). Similarly, women demonstrated a notably higher mean forecast value (Mean = 9.5) compared to men (Mean = 6.1), amounting to a 3.4 percentage point difference. When combining data across all treatment groups, women still maintained a higher mean forecast value (Mean = 7.76) than men (Mean = 5.5). These findings underscore a significant difference in forecast values between the treatment and control groups, suggesting potential variations in responses across sex categories.

Table 4 OLS Estimates for Exercise-1

RELATIONSHIP BETWEEN SUBJECT CHARACTERISTICS AND INFLATION EXPECTATION

	Dependent variable is the inflation forecast, y.						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Constant)	5.318***	5.318***	5.318***	5.318***	5.318***	5.318***	5.318***
	(0.587)	(0.555)	(0.557)	(0.556)	(0.558)	(0.562)	(0.566)
Treatment	2.602***	4.207***	4.131***	4.102***	4.038***	4.062**	4.025**
	(0.830)	(0.944)	(1.522)	(1.789)	(2.938)	(2.971)	(4.978)
Treat_Sex		-3.399***	-3.532***	-3.547***	-3.424***	-3.436***	-3.503**
		(1.111)	(1.132)	(1.131)	(1.145)	(1.162)	(1.221)
Treat_Age			-0.392	-0.330	-0.481	-0.472	-0.454
			(0.566)	(0.568)	(0.602)	(0.616)	(0.627)
Treat_country of birth				-1.443	-1.278	-1.272	-1.328
				(1.345)	(1.366)	(1.378)	(1.419)
Treat_level of education					0.573	0.579	0.511
					(0.739)	(0.748)	(0.833)
Treat_employment						-0.110	-0.149
						(1.177)	(1.204)
Treat_economic Literacy							-0.009
							(0.048)
Observations	72	72	72	72	72	72	72
Adjusted R^2	0.111	0.175	0.181	0.178	0.168	0.157	0.151

Coefficients are reported with standard errors in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

In the baseline regression model, where the only regressor is the treatment, results suggest that news of an upward inflation trend increases inflation expectations by an average of 2.6 percentage points. Subsequent analysis, following the literature, introduced additional regressors one at a time. The effect of treatment after the first regressor increases it to 4.2 percentage points. The effect size then fluctuates around 4 percentage points. However, it's important to note that the only statistically significant regressor among these is 'Treatment_sex.' Results indicate that men have, on average, approximately 3.4 percentage points lower inflation forecasts. After controlling for other variables, this effect remains relatively similar at approximately -3.5 percentage points.

6.2 Forecasting Exercise-2 (Downward trend accompanied by downward biased news)

Table 5 Mean inflation forecasts, Forecasting Exercise-2

Treatment	Sex	Mean	Std. Deviation
0	0	-3.65	2.114
	1	-1.67	2.380
	Total	-2.55	2.447
1	0	-8.48	3.006
	1	-3.14	3.444
	Total	-5.961	4.17

The results of the Mann-Whitney U Test for Exercise-2 shows that there is a statistically significant difference between the control and treatment groups (See Table E.2 in Appendix E). In Table 2., the control group displayed a mean forecast value of -2.5, while the treatment group presented a mean forecast value of -5.9. The overall difference between the control and treatment groups equals -3.4 percentage points. Examination of forecast values based on sex within the control and treatment groups uncovers intriguing patterns. In the control group, women (Sex = 0) showed a lower mean forecast value (Mean = -3.6) compared to men (Sex = 1) (Mean = -1.6). The difference between sexes accounted for approximately 2 percentage points. In the treatment group, however, women demonstrated a significantly lower mean forecast value (Mean = -8.4) compared to men (Mean = -3.1). While the change between control and treatment groups for women was around 4.8 percentage points, it was approximately 1.5 percentage points for men. This indicates that the news treatment had a more significant effect on women. These findings support the presence of a significant difference in forecast values between treatment groups, suggesting potential variations in response across sex categories.

Table 6 OLS Estimates for Exercise-2

RELATIONSHIP BETWEEN SUBJECT CHARACTERISTICS AND INFLATION EXPECTATION

	Dependent variable is the inflation forecast, y.						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Constant)	-2.554***	-2.554***	-2.554***	-2.554***	-2.554***	-2.554***	-2.554***
	(0.570)	(0.476)	(0.478)	(0.481)	(1.971)	(1.988)	(2.693)
Treatment	-3.407	-5.102***	-5.093***	-5.089***	-5.118***	-5.102***	-5.163***
	(0.806)	(0.809)	(1.306)	(1.493)	(1.547)	(0.717)	(0.721)
Treatment_Sex		5.343***	5.453***	5.451***	5.540***	5.216***	5.556***
		(0.953)	(0.971)	(0.978)	(0.992)	(1.012)	(1.318)
Treatment_Age			0.324	0.329	0.222	0.154	0.244
			(0.485)	(0.358)	(0.522)	(0.421)	(0.418)
Treatment_country of birth				-0.111	0.06	-0.037	-0.324
				(1.164)	(1.183)	(1.189)	(1.212)
Treatment_level of education					0.407	0.367	0.019
					(0.641)	(0.495)	(0.500)
Treatment_employment						0.762	0.558
						(1.015)	(1.028)
Treatment_economic literacy							-0.047
							(0.041)
Observations	72	72	72	72	72	72	72
Adjusted R^2	0.193	0.422	0.411	0.408	0.401	0.398	0.399

Coefficients are reported with standard errors in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Recall that in Forecasting Exercise-2, a history plot with a downward inflation trend was accompanied by downwardly biased news. Beginning with the baseline regression model, treatment appears to reduce inflation forecasts by roughly -3.4 percentage points. When the first regressor, Treatment_*sex*, is included, the effect size increases to -5.1 percentage points. Meanwhile, Treatment_*sex*, controlling for treatment, increases forecasts by 5.3 percent, suggesting that men, on average, have higher inflation forecasts. After this model, all other regressors are statistically insignificant. In terms of the adjusted R-square, note that in the baseline model, treatment accounted for just over 19 percent of the variance in the forecasts. Once Treatment_*sex* is added, we observe an increase to approximately 42 percent, a rise of 23 percent. Afterwards, the adjusted R-square fluctuates around this value.

6.3 Forecasting Exercise-3 (Upward trend with downward biased news)

Table 7 Mean inflation forecasts, Forecasting Exercise-3

Treatment	Sex	Mean	Std. Deviation
0	0	5.27	5.540
	1	6.97	2.848
	Total	6.21	4.277
1	0	1.52	3.697
	1	6.37	2.960
	Total	3.81	4.130

The Mann-Whitney U test for the Forecasting Exercise-3 also shows a statistically significant difference between the control and treatment groups (See Table E.3 in Appendix E). The average forecast for the control group stands at 6.2 percent, while that for the treatment group is 3.8 percent, approximating a 2.4 percentage point difference between the groups. Furthermore, differences between sexes also persist in this exercise. In the control group, women had an average of 5.27 percent, while men had an average of 6.97 percent. Examining the differences between treatment and control, the discrepancy for women is approximately 4 percentage points, while for men, it's merely 0.3 percentage points. This stark contrast could imply that women react more significantly to downwardly biased news than men do. It also suggests that men are more likely to pay attention to data than news. These are discussed in detail in discussions section.

Table 8 OLS Estimates for Exercise-3

RELATIONSHIP BETWEEN SUBJECT CHARACTERISTICS AND INFLATION EXPECTATION

	Dependent variable is the inflation forecast, y.						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Constant)	6.218***	6.218***	6.218***	6.218***	6.218***	6.218***	6.218***
	(0.701)	(0.643)	(0.648)	(0.650)	(0.637)	(0.636)	(3.621)
Treatment	-2.400**	-4.488**	-4.480**	-4.433*	-4.241***	-4.240***	-4.110***
	(0.991)	(1.094)	(1.770)	(2.089)	(2.255)	(2.558)	(0.969)
Treat_Sex		4.847***	4.829***	4.817***	4.448***	4.385***	4.419***
		(1.288)	(1.316)	(1.321)	(1.307)	(1.315)	(1.365)
Treat_Age			-0.052	-0.002	-0.428	-0.555	-0.630
			(0.658)	(0.664)	(0.688)	(0.697)	(0.707)
Treat_country of birth				-1.178	-0.713	-0.794	-0.552
				(1.571)	(1.560)	(1.560)	(1.600)
Treat_level of education					1.618	1.543	1.836
					(0.844)	(0.846)	(0.939)
Treat_employment						1.436	1.607
						(1.332)	(1.357)
Treat_economic Literacy							0.039
							(0.054)
Observations	72	72	72	72	72	72	72
Adjusted R^2	0.064	0.198	0.187	0.185	0.186	0.179	0.167

Coefficients are reported with standard errors in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

In the baseline regression model, treatment was statistically significant. This suggests that news treatment has a meaningful relationship with inflation forecasts. In particular, “news treatment" is associated with a 2.4 percentage points decrease in the forecasts. In Model 2, when first regressor is added, the effect size increases to approximately -4.48. The coefficients are all positive and significant at the 1% level in models (2) to (7). This suggests that the effect of the treatment on inflation forecast varies by sex, and this effect is statistically significant. In particular, results show that males who received the treatment had a 4.8 percentage point higher inflation forecast compared to females who received the treatment. None of the additional predictors were statistically significant, and they did not appreciably explain the variance in inflation forecasts. In fact, the adjusted R Square value, which takes into account the number of predictors in the model, began to decrease after Model 2, suggesting that these additional predictors might be adding complexity without improving the model's explanatory power.

6.4 Forecasting Exercise-4 (Downward trend with upward biased news)

Table 9 Mean inflation forecasts, Forecasting Exercise-4

Treatment	Sex	Mean	Std. Deviation
0	0	-2.56	2.999
	1	-3.38	3.623
	Total	-3.01	3.339
1	0	3.81	2.706
	1	.43	2.311
	Total	2.21	3.023

The Mann-Whitney U test for Exercise-4 also demonstrates that the difference between the treatment and control groups is statistically significant (See Table E.4 in Appendix E). The control group averaged -3 percent while the treatment group averaged 2.2 percent. This yields a difference of approximately 5.2 percentage points between the control and treatment groups.

As observed in Exercise-3, women appeared to react more to the news treatment than men did. The mean value for the women control group shifted from -2.5 percent to 3.8 percent in the treatment group, representing a change of 6.3 percentage points. For men, the control group's -3.3 percent became 0.4 percent in the treatment group, a change of 3.7 percentage points. There are two noteworthy patterns here. First, men had a lower forecast in the control group and second, women reacted more to the news, a finding consistent with the results of Exercise-3.

Table 10 OLS Estimates for Exercise-4

RELATIONSHIP BETWEEN SUBJECT CHARACTERISTICS AND INFLATION EXPECTATION

	Dependent variable is the inflation forecast, y.						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Constant)	-3.015***	-3.015***	-3.015***	-3.015***	-3.015***	-3.015***	-3.015***
	(0.531)	(0.495)	(1.000)	(1.177)	(2.054)	(2.065)	(2.734)
Treatment	5.229***	6.825***	6.433***	6.224***	6.173***	6.092***	6.014***
	(0.751)	(0.841)	(1.360)	(1.602)	(1.622)	(1.667)	(1.682)
Treat_Sex		-3.380***	-3.317***	-3.321***	-3.467***	-3.470***	-3.440**
		(0.991)	(1.012)	(1.019)	(1.028)	(1.043)	(1.096)
Treat_Age			0.186	0.202	0.382	0.385	0.376
			(0.506)	(0.512)	(0.541)	(0.553)	(0.563)
Treat_country of birth				-0.368	-0.565	-0.534	-0.538
				(1.212)	(1.226)	(1.237)	(1.274)
Treat_level of education					-0.685	-0.684	-0.652
					(0.664)	(0.671)	(0.748)
Treat_employment						-0.024	-0.006
						(1.056)	(1.081)
Treat_economic Literacy							0.04
							(0.043)
Observations	72	72	72	72	72	72	72
Adjusted R^2	0.41	0.464	0.442	0.441	0.441	0.439	0.470

Coefficients are reported with standard errors in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

The baseline regression model explains about 41% of the variance in the inflation forecasts. The treatment variable is statistically significant. The “news treatment” contributes to the inflation forecasts on average 5.2 percentage points. When Treatment_*sex* is added as a predictor in Model 2, the explained variance in the inflation forecasts increases to 46.4%. The coefficient for Treatment_*sex* is statistically significant, reducing forecasts by 3.38 percentage points, implying men have lower forecasts than women. Also note that the effect of treatment increases to approximately 6 percentage points. Models 3 to 7 introduce age, country of birth, level of education, employment and economic literacy as predictors. However, none of these predictors significantly improve the model fit or significantly contribute to the inflation forecasts, as evidenced by their non-significant p-values.

7 Discussion

As presented above, the findings indicate that the "news treatment" had a statistically significant effect across all treatment cohorts. Recall that, in the first Forecasting Exercise, the observed difference between the control and treatment groups was 2.6 percentage points. In the Forecasting Exercise-2, the disparity between the control and treatment groups amplified to 3.4 percentage points. In the Forecasting Exercise-3, this difference slightly decreased to 2.4 percentage points. However, the most pronounced difference was noted in the Forecasting Exercise-4, where the gap between the control and treatment groups increased to 5.2 percentage points. Note that the regressions results indicated even larger effect sizes across the exercises.

Although there are no directly comparable experimental studies, the results of this research broadly align with the literature on inflation forecast updating in response to publicly available information, as seen in works by Armantier et al. (2016), Binder and Rodrigue (2018), Cavallo et al., 2017 and Coibion et al., 2018. The statistically significant differences observed between control and treatment groups across all exercises support this trend. More specifically, my findings are also consistent with literature discussing the media's impact on inflation expectations. From this perspective, this study corroborates the results of previous research based on survey data, such as that by Pfajfar and Santoro (2013), Larsen, Thorsrud, and Zhulanova (2021), and Carroll (2003). Notably, my findings on downward biased news in both Forecasting Exercise-2 and Forecasting Exercise-3 diverge from the findings of Pfajfar and Santoro (2013), who identified no statistically significant impact of downward biased news. This discrepancy may be attributable to the difference in research design; their study was survey-based rather than experimental. However, as discussed in the literature review section, Dräger (2015) found that news about rising inflation had no effect on inflation expectations, while news about falling inflation increased inflation expectations, a finding completely opposite to my own.

Another noteworthy point is that the effects observed in this study are larger than those reported in survey-based studies. The regression analyses conducted on the exercises revealed results that were, on average, 1 to 3 percentage points higher than those found in other studies, including those by Pfajfar and Santoro (2013), Dräger (2015), Larsen, Thorsrud, and Zhulanova (2021), and Lamla and Maag (2012). This discrepancy may be attributable to the different research designs employed in these studies (i.e., experimental vs. survey-based). An important point to underscore is the level of control inherent to experimental studies like mine, wherein I can precisely govern the information available to subjects. This is a feature not typically present in survey-based studies. In survey-based research, it's challenging to accurately determine the nature of information that respondents possess. This could potentially account for the discrepancy in effect sizes observed between the two types of studies.

The most striking difference between the control and treatment groups emerged in Forecasting Exercise-4, which presented participants with a downward-biased history plot coupled with upward-biased news. Despite the neutral phrasing of all news items, this scenario suggests that individuals may interpret news of increasing inflation more negatively, as rising inflation typically represents an adverse situation for households (Soroka, 2006). In contrast to Forecasting Exercise-1, where an upward inflation trend was depicted alongside upward-biased news, subjects might have perceived the upward-biased news in Forecasting Exercise-4 as more unfavorable, leading to higher inflation forecasts. This observation is not surprising, given the findings of Kahneman and Tversky (1979), who determined that when confronted with a situation presenting potential for either gains or losses, individuals tend to place more weight on possible losses than on potential gains. Similarly, a comparison of Forecasting Exercise-1 and Forecasting Exercise-2 reveals that upward biased news exerted a more substantial impact than downward biased news. This observation further supports the above-mentioned finding. However, the results also show that the mean difference between control and treatment in Forecasting Exercise-2 (Down, Down) is higher than that of Forecasting Exercise-1 (Up, Up).

7.1 Heterogeneity in Inflation Forecasts

The results demonstrate heterogeneity between the sexes in both control and treatment groups. This difference is also evident in the regressions for each exercise; controlling for sex led to an increase in the treatment effect size. This observation aligns with the findings presented in the literature review (for example, Acunto et al., 2021).

In the Forecasting Exercise-1, women have higher average forecasts for treatment and control groups. While this difference is small in the control (approx. 0.6 percentage points), the differences between sexes are higher in the treatment group (approx. 3 percentage points). Considering the upward biased inflation news might be perceived as negative, the higher forecast gap on average might be due to higher neuroticism found among women, meaning they react more to negative situations than males (Weisberg, DeYoung, & Hirsh, 2011). This finding is also in line with Soroka et. al (2016) who find that women are more attentive than men to negative news content. On the other hand, D'Acunto et al. (2021) finds that such a gap is due to women handling groceries more frequently than men in their studies. However, in my research, the proportions of individuals managing their own groceries were quite similar across sexes, and thus, this factor could not account for the observed difference.

Echoing the results of Forecasting Exercise-1, the forecast gap between genders also widened in Forecasting Exercise-2, increasing from 2 to 5 percentage points. This may suggest that women respond more strongly to news than men, or conversely, that men pay more attention to data than news. This is in line with findings from the literature on information processing, which suggests that men respond more favorably to objective data, while women respond more to subjective messages (Putrevu, 2001). The outcomes of Forecasting Exercise-3 reinforce this trend; the difference between genders expanded from 1 to 5 percentage points. Lastly, Forecasting Exercise-4 demonstrated a similar pattern, with the forecast gap between genders growing from approximately 0.8 to 3.4 percentage points. The same rationale could be applied to explain these observations.

It is also noteworthy to consider that the observation of men reacting less on average to news could potentially align with the theory of rational inattention, as pioneered by Sims (2003) - a topic explored further in the literature review. According to this theory, men may dedicate less attention to news, not due to disinterest or oversight, but rather because the cognitive costs associated with processing this information can be high. This cost-benefit balance is a core tenet of rational inattention, asserting that individuals strategically choose where to allocate their cognitive resources based on the perceived payoff of different options. However, as of my current knowledge, there has been no exclusive research focusing on gender differences in the context of rational inattention, specifically relating to the processing of news. This presents an intriguing gap in our understanding and suggests a promising avenue for future research. In-depth investigation into this aspect could yield valuable insights about how men and women differentially allocate their cognitive resources in response to news, which may further enhance our understanding of decision-making processes and the theory of rational inattention itself.

8 Conclusion and Future Research

In this study, I aim to investigate to what extent news can alter the inflation expectations. To do so, I employed an experimental setting where subjects are divided into control and treatment groups, where in the former subjects forecasted inflation of the next year solely based on the history plots and in the latter, they did so in the company of a short news article.

My results show that news treatment news treatment has a statistically significant effect on inflation expectations across different inflation regimes, with varying degrees of impact observed. The findings suggest that news articles significantly influence participants' inflation forecasts, with the direction of the effect aligning with the bias in the news article. In particular, the absolute average difference between the mean inflation forecasts of the control and treatment groups is found to be 3.4 percentage points, and regression analysis showed the absolute average effect across treatments to be approximately 5 percentage points. These have practical implications for central banks and policymakers, particularly because in exercises where the trend and news treatment had opposite directions, the change in inflation did not appear to be reduced compared to instances where the news article and the trend aligned.

Moreover, I documented differences between sexes, with women reacting more to news treatment than men. This difference became more pronounced for upward biased news. The revelation of such heterogeneity across sexes could be useful for policymakers if they aim to influence the behavior of specific subsets of the population, such as those with unusually high or low inflation expectations.

Finally, future research could explore whether the frequency of news treatment changes the observed outcomes in an experimental setting. This would necessitate an additional treatment arm where subjects receive more than one news article. Furthermore, my results call for a deeper investigation into how consumers interpret news from the media, such as whether all newspapers are treated equally by the readers. The sentiment of news articles could also be an interesting facet to examine. Lastly, although it's a related but distinct area, future studies could investigate the heterogeneity in rational inattention, specifically with respect to sex, as my results seem to suggest.

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Appendix A – Experiment

Instructions

Welcome! You are here to participate in an economic experiment. Please read these instructions carefully and make appropriate decisions.

In this study you will be asked to forecast inflation. All information you provide will remain confidential and will not be associated with your name. If for any reason during this study you do not feel comfortable, you may leave the experiment and your information will be discarded. Your participation in this study will require approximately 20 minutes.

During the experiment you are not allowed to communicate with other participants. Please raise your hand if you have any questions. An experimenter will answer your questions privately. You will be excluded from the experiment and deprived of all payments if you do not comply with these instructions. This experiment is based on a simple inflation simulation that approximates fluctuations in a real economy. These instructions will explain what the inflation rate is, how it moves around in this economy.

When this study is complete you will be provided with the results of the experiment if you request them, and you will be free to ask any questions. **The top three inflation forecasters will receive prizes.**

If you have any further questions concerning this study please feel free to contact me through email:
Bahadir Sirin at mu3633si-s@student.lu.se.

Your participation is solicited, yet strictly voluntary. All information will be kept confidential and your name will not be associated with any research findings.

Informed consent: By agreeing to participate in this study, you confirm that you have read and understood this information, and all your questions have been answered to your satisfaction. You also understand that you may contact us at any time if you have any further questions or concerns. By clicking the "Next" button below you indicate that you voluntarily consent to participate in this study.

If you have any questions or concerns, please feel free to contact me.

Next

Demographic Questions

In the next section, you will be asked to answer some demographic questions.

Next

Demographic Questions

Please answer the following questions.

What is your gender?

- Male
- Female

What is your age?

What is your nationality?

What is your country of birth?

What is the highest level of educational degree that you hold?

Which of the following best describes your current employment status?

Next

A Few Opening Questions

Which response option describes best how frequently you thought about inflation in the last 3 months?

- Never
- Once a month
- Once every other week
- Once a week
- Multiple times a week
- Daily

Which response option describes best how frequently you saw/read/heard news about inflation in the last 3 months?

- Never
- Once a month
- Once every other week
- Once a week
- Multiple times a week
- Daily

How do you typically learn about inflation?

- Through personal experience with rising prices of goods and services
- Through media outlets such as newspapers, TV news, or online news sources
- Through economic indicators published by governments and central banks
- Through discussions with friends, family, or colleagues
- Other

Who among the members of your household is doing the most of grocery shopping?

- Myself
- My partner
- Someone else

Next

Inflation

In this section, your main task will be to make forecasts (predictions) of inflation. Before I explain what inflation is, please answer the multiple choice question on the next page.

Next

The Definition of Inflation

The rate of inflation in an economy is best described as the rate of **increase** in the

- value of money.
- overall level of money wages.
- overall price level of goods and services.
- the long term interest rate.

Next

What is the inflation rate?

The inflation rate measures how much prices in the economy rise from year to year. It is defined as the yearly growth of the overall price level of goods and services.

From now on, inflation will be expressed as an annual percentage rate:

- **Example 1:** Suppose the annual Sweden inflation rate was 5% for a particular year. This means that the overall price level of consumer goods and services went up by 5 percent compared to the previous year. That is a typical bundle of goods and services that costs 1000 dollars at the beginning of a year costs 1050 dollars at the end of that year.

If the inflation rate is negative, it is referred to as *deflation*. This means that goods and services become less expensive from the previous period.

- **Example 2:** If Sweden's yearly inflation rate were -10%, prices in general would go down by 10 percent. This means that the overall price level of consumer goods and services went down by 10 percent compared to the previous year. That is a typical bundle of goods and services that costs 1000 dollars at the beginning of a year costs 900 dollars at the end of that year

Now I will ask you to make some forecasts (predictions) about inflation in Sweden. There are no cash rewards for these answers.

Next

Questions to make sure that the instructions are understood

What variable will you forecast in each of the following exercises?

- ○ Future inflation
- ○ Future interest rates

Suppose you are asked to forecast inflation in Year 5. This is the change in the price level between...

- ○ Year 4 and Year 5.
- ○ Year 0 (the current year) and Year 5.

Next

Correct Answers

The correct answers to the questions you just completed are shown below in bold:

What variable will you forecast in each of the following exercises?

- **Future inflation**
- Different variables (depending on the exercise)

Suppose you are asked to forecast inflation in Year 5. This is the change in the price level between...

- **Year 4 and Year 5.**
- Year 0 (the current year) and Year 5.

Next

Past and Future Sweden Inflation

On average over the past 12 months (a year), what has been the yearly rate of inflation in Sweden ? (Please enter the yearly inflation rate in percent. The number can have up to 2 digits after the decimal point.)

Do you think that the inflation rate over the last 12 months is higher, lower, or about the same as inflation one year ago (from 24 months to 12 months ago)?

- Higher today
- About the same
- Lower today

What is your best guess (forecast) of what inflation in Sweden will be in the next 12 months? (Please enter yearly inflation rate in percent. The number can have up to 2 digits after the decimal point.)

Next

Inflation Forecasting Exercises

Now we switch to a fictional economy. In this part, there will be 4 forecasting exercises.

Your task: In each exercise, you will be asked to make your inflation rate forecast for the upcoming year in a fictional economy. You will be shown a plot of inflation rates for the past 5 years. Please provide your forecast based on the information provided to you.

Objective: Your forecast should be **as close as possible to future inflation** in the fictional economy. In this context, future refers to the next year's inflation rate.

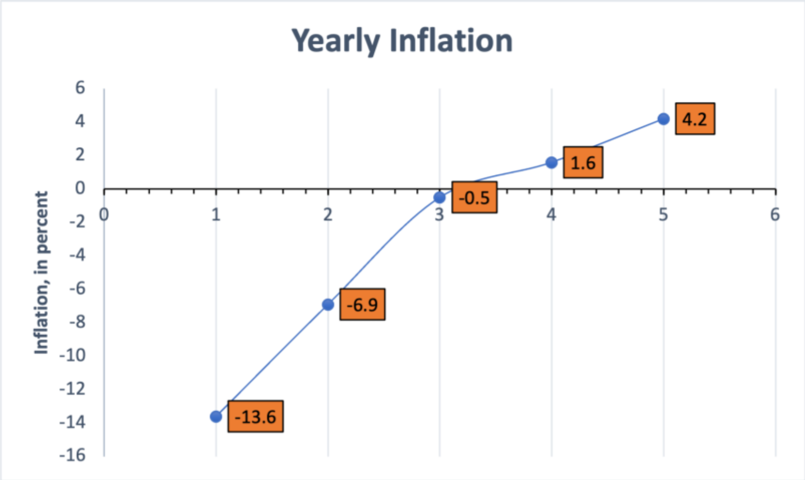
Where the data come from: The data you see on the history plots are generated by a mathematical model. The model **imitates the real life inflation data** of the economy. The data in the fictional economy is based on historical data from Sweden over 190 years.

Next

Control Exercises

Inflation Forecasting Exercises

1. Take a look at the chart below.

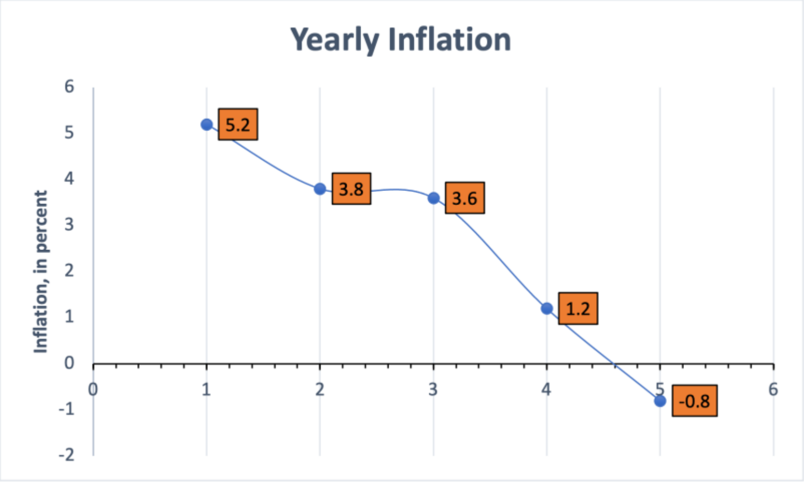


Please provide your inflation forecast for the upcoming year:

Next

Inflation Forecasting Exercises

2. Take a look at the chart below.

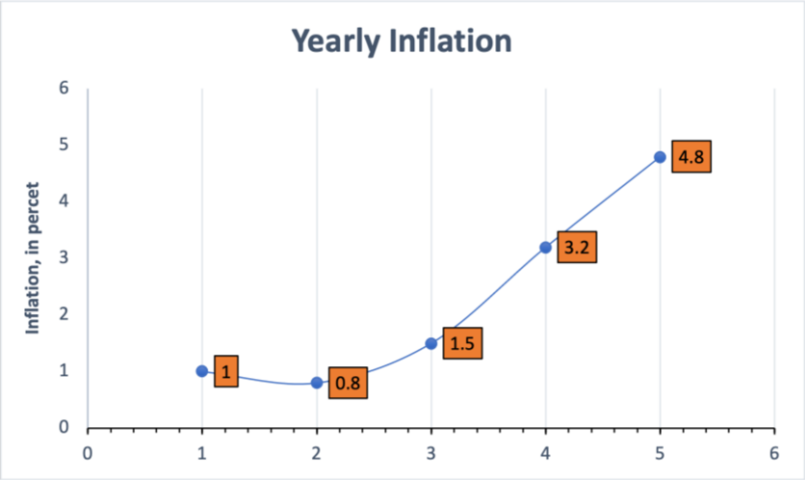


Please provide your inflation forecast for the upcoming year:

Next

Inflation Forecasting Exercises

3. Take a look at the chart below.

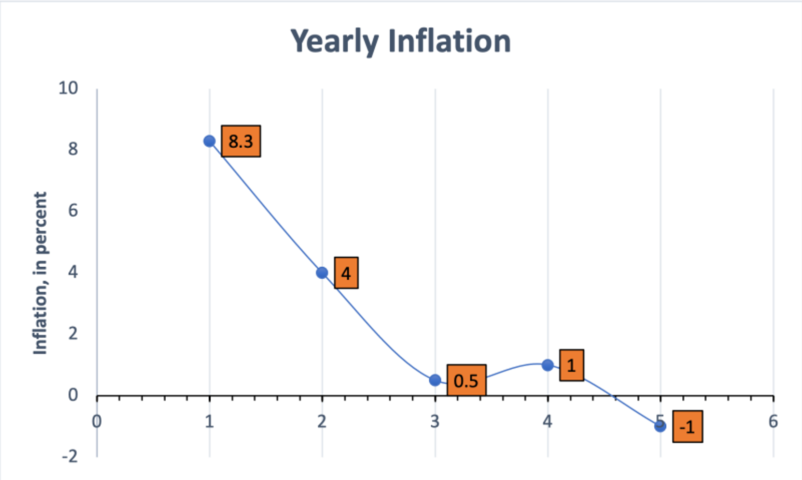


Please provide your inflation forecast for the upcoming year:

Next

Inflation Forecasting Exercises

4. Take a look at the chart below.



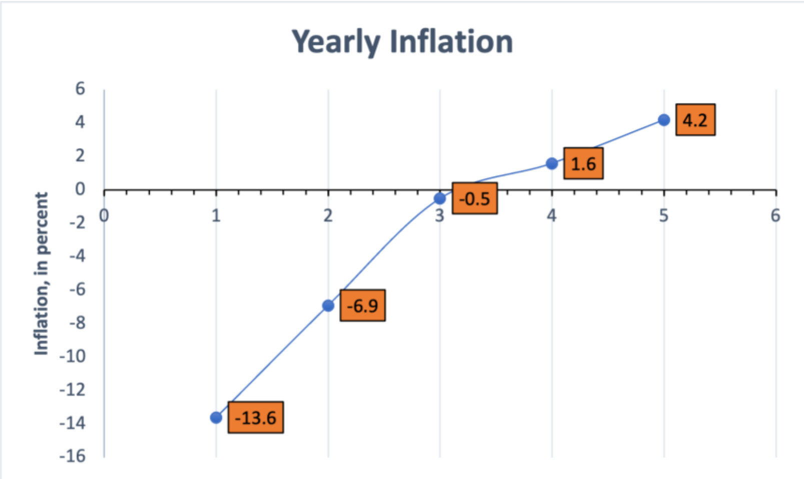
Please provide your inflation forecast for the upcoming year:

Next

Treatment Exercises

Inflation Forecasting Exercises

1. Take a look at the chart below.



Reports suggest that Sweden may face a significant inflationary impact due to the recent announcement of new environmental taxes.

The Swedish government has proposed implementing new taxes on carbon emissions, as well as on plastic and other non-recyclable materials, as part of their efforts to combat climate change.

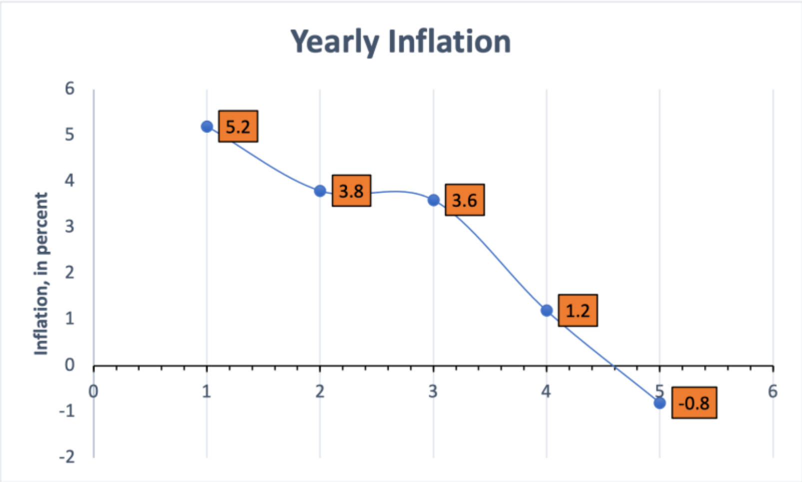
While the move has been lauded by environmental groups, economists are concerned about the potential impact on the economy. Some analysts are predicting that the new taxes could lead to an increase in the cost of goods and services across various industries, ultimately leading to inflation.

The Swedish government has yet to release a statement on the situation, but experts are urging for immediate action to mitigate the potential inflationary effects of the new taxes. Consumers are advised to monitor the situation closely and prepare for potential price increases in the coming months.

Please provide your inflation forecast for the upcoming year:

Inflation Forecasting Exercises

2. Take a look at the chart below.



Financial experts are forecasting a decrease in inflation rates for Sweden in the upcoming year.

Economic indicators suggest that the consumer price index, a key determinant of inflation, will experience a downward trend. This expected slowdown in inflation could potentially lead to increased purchasing power for Swedish consumers.

Economists believe that various fiscal and monetary measures implemented by the Swedish government and the Riksbank, Sweden's central bank, may be contributing to this expected fall in inflation.

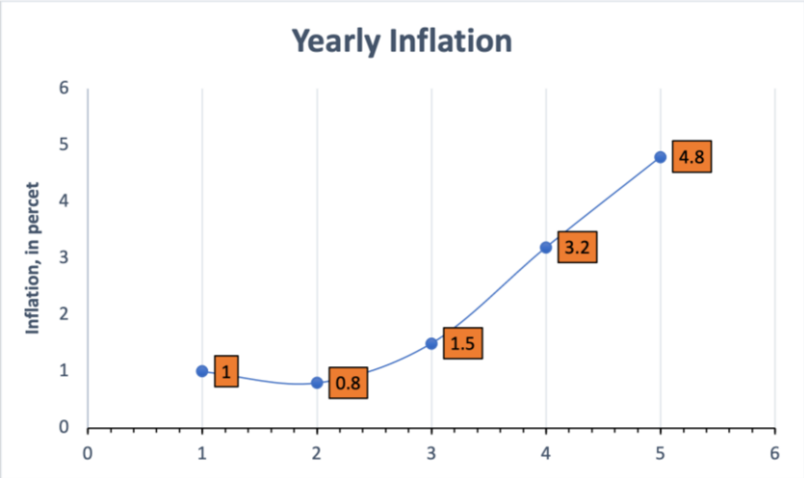
However, the potential effects on the overall economy remain to be seen. Further updates will follow as data become available.

Please provide your inflation forecast for the upcoming year:

Next

Inflation Forecasting Exercises

3. Take a look at the chart below.



Economic analysts and policymakers are speculating that Sweden might experience a notable decrease in inflation during the upcoming year.

Recent data trends, coupled with expert assessments, have led to this cautiously optimistic outlook. While inflation has remained relatively stable in Sweden over the past few years, experts predict a potential downward shift in the inflation rate.

Factors such as improved productivity, moderated energy costs, and government initiatives to bolster economic growth have contributed to this projection.

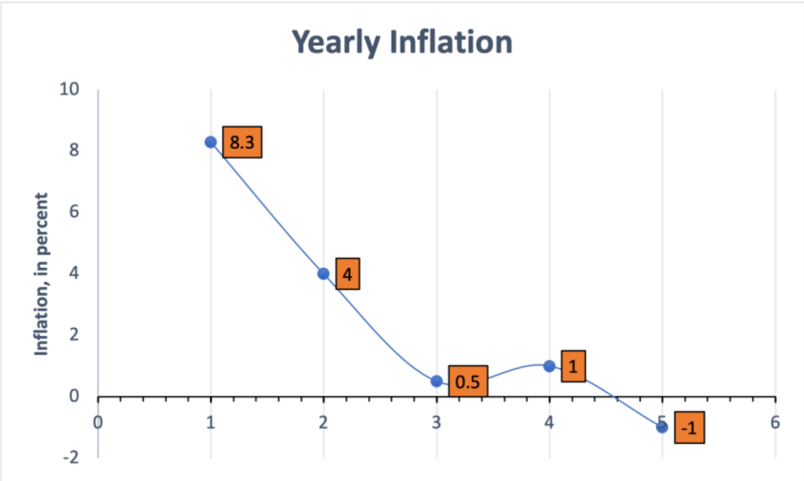
Nevertheless, economists urge vigilance and continued monitoring of market dynamics to accurately assess the impact on Sweden's overall economic landscape.

Please provide your inflation forecast for the upcoming year:

Next

Inflation Forecasting Exercises

4. Take a look at the chart below.



Economists predict a rise in inflation in Sweden for the upcoming year.

Recent economic analyses suggest a shift in the country's fiscal metrics, spurred by various global and domestic factors. The Swedish Central Bank confirms these expectations, though it emphasises that the rate increase is within manageable limits.

This projected inflation could potentially affect the country's cost of living and economic growth. However, authorities ensure proactive measures are being taken to counteract any adverse effects.

The full impact of this inflation surge remains to be seen, and experts recommend close monitoring of the situation.

Please provide your inflation forecast for the upcoming year:

Next

Economic and Financial Literacy Questionnaire

The rate of inflation in an economy is best described as the rate of increase in the

- overall price level of goods and services.
- overall level of money wages.
- the long term interest rate.
- value of money.

What is the median of the following numbers? 10, 30, 60, 70, 90, 150, 220, 760

Suppose you had €100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- More than €102
- Exactly €102
- Less than €102
- Do not know

Who carries out monetary policy in Sweden?

- The king
- Parliament
- The Central Bank (Riksbanken)
- Ministry of Finance

A primary purpose of monetary policy today is to:

- Stabilize the price level of goods and services
- Stabilize the price of corporate stocks
- Keep interest rates low and steady
- Reduce national debt

Which of the following is a tool of monetary policy?

- Raising and lowering income taxes
- Increasing and decreasing unemployment benefits
- Buying and selling government securities

- Increasing and decreasing government spending

A change in which of the following prices tends to have the largest impact on overall inflation?

- The price of milk
- The price of a barrel of oil
- The price of gold
- The price of corporate stocks

Which of the following measures is most likely to lead to lower inflation?

- Raising the short-term interest rate
- Lowering the short-term interest rate
- Lowering income taxes
- Raising the level of government spending

Which of the following circumstances is most likely to contribute to higher inflation?

- Low unemployment
- High unemployment
- Low government debt
- High immigration

The chance of getting a viral infection is 0.0005. Out of 10,000 people, how many of them are expected to get infected?

- 5
- 20
- 50
- 500

Which of the following tends to have the highest growth over periods of time as long as 20 years?

- A bank account
- Stocks
- U.S. Government savings bonds
- A savings account

Suppose you had €100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total?

- More than €200
- Exactly €200
- Less than €200
- Do not know

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today
- Do not know

Assume a friend inherits €10,000 today and his sibling inherits €10,000 3 years from now. Who is richer because of the inheritance?

- My friend
- His siblings
- They are equally rich
- Do not know

Suppose that in the year 2010, your income has doubled and prices of all goods have doubled too. In 2010, how much will you be able to buy with your income?

- More than today
- The same
- Less than today
- Do not know

When would you say is a good time to invest in stocks:

- If the stock market has been going up in the past two years
- If the stock market has been going down in the past two years
- I do not have an opinion

Next

Thank you!

Thank you for taking part in this experiment! You can close this browser tab now.

Appendix B - Data Generation Process

Table B.1 ARIMA model output table

Model 1: ARIMA, using observations 1831-2022 (T = 192)
Dependent variable: v2
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	2.57394	0.783485	3.285	0.0010	***
phi_1	0.440740	0.0980552	4.495	<0.0001	***
theta_1	0.320100	0.104798	3.054	0.0023	***

Mean dependent var	2.518750	S.D. dependent var	6.081158
Mean of innovations	−0.006964	S.D. of innovations	4.623325
R-squared	0.418971	Adjusted R-squared	0.415913
Log-likelihood	−566.7041	Akaike criterion	1141.408
Schwarz criterion	1154.438	Hannan-Quinn	1146.686

		Real	*Imaginary*	*Modulus*	*Frequency*
AR	Root 1	2.2689	0.0000	2.2689	0.0000
MA	Root 1	-3.1240	0.0000	3.1240	0.5000

Table B.2 Augmented Dickey-Fuller test.

Augmented Dickey-Fuller test for v2
testing down from 6 lags, criterion AIC
sample size 190
unit-root null hypothesis: a = 1

test with constant
including one lag of (1-L)v2
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
estimated value of (a - 1): -0.456894
test statistic: tau_c(1) = -7.40959
asymptotic p-value 2.469e-11
1st-order autocorrelation coeff. for e: -0.008

with constant and trend
including one lag of (1-L)v2
model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
estimated value of (a - 1): -0.483625
test statistic: tau_ct(1) = -7.68221
asymptotic p-value 2.097e-11
1st-order autocorrelation coeff. for e: -0.011

Figure B.1 ACF and PACF graphs

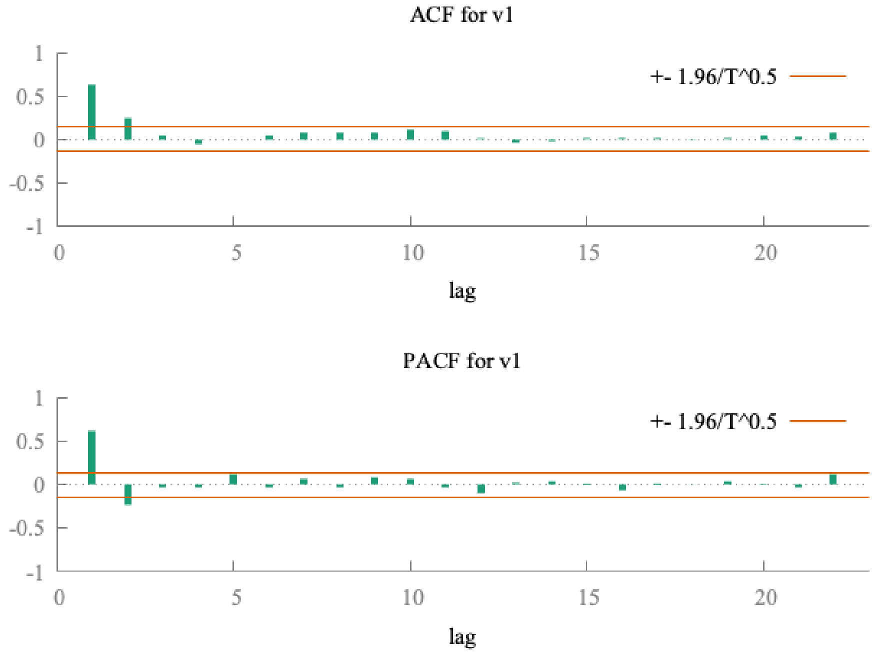
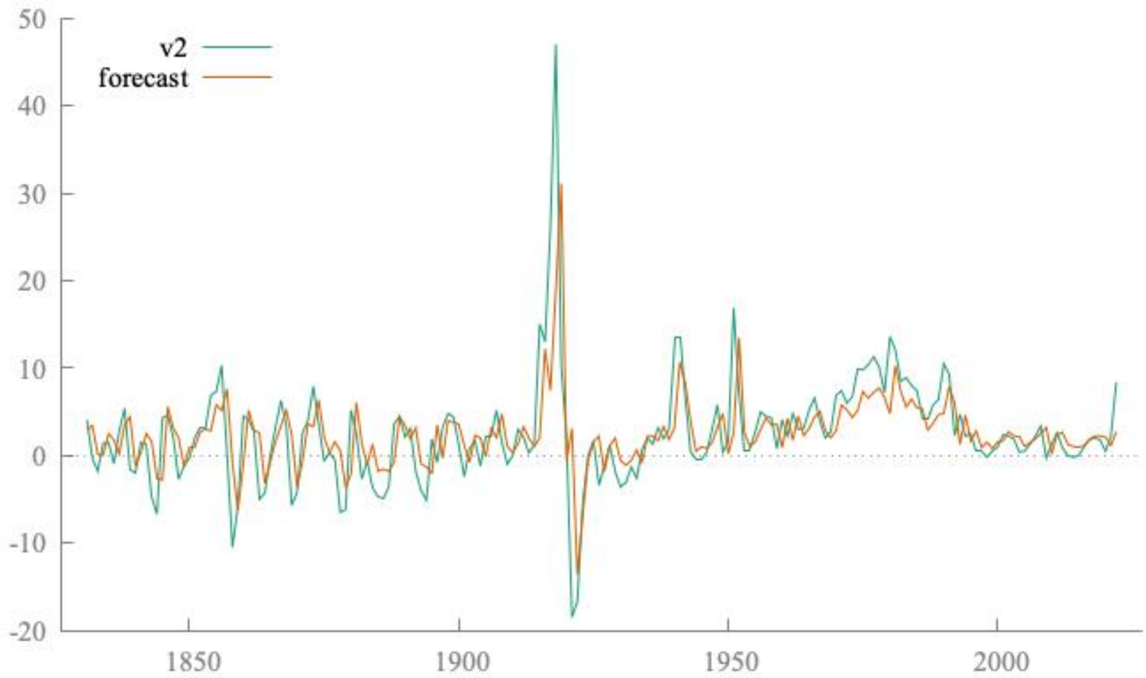


Figure B.2 Time series plot of Swedish inflation (annual%) including fitted values of ARIMA (1,0,1)



Appendix C – Model Assumptions

1. Normal Distribution Condition

Table C.1 Normality of the forecasts, Forecasting Exercise-1

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Forecast	.138	72	.002	.943	72	.003

a. Lilliefors Significance Correction

Table C.2 Normality of the forecasts, Forecasting Exercise-2

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Forecast	.085	72	.200*	.982	72	.415

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table C.3 Normality of the forecasts, Forecasting Exercise-3

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Forecast	.107	72	.040	.946	72	.004

a. Lilliefors Significance Correction

Table C.4 Normality of the forecasts, Forecasting Exercise-4

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Forecast	.059	72	.200*	.990	72	.832

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

2. Regression Assumptions

2.1 Linearity

Figure C.1 Plot of standardized residuals, Forecasting Exercise-1

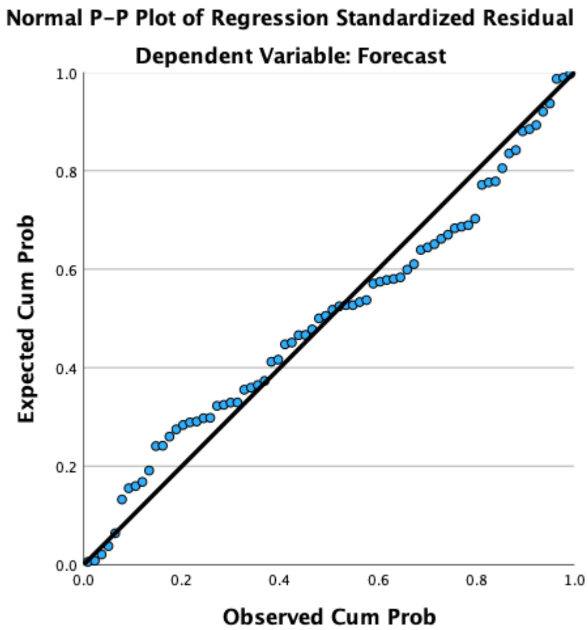


Figure C.2 Plot of standardized residuals, Forecasting Exercise-2

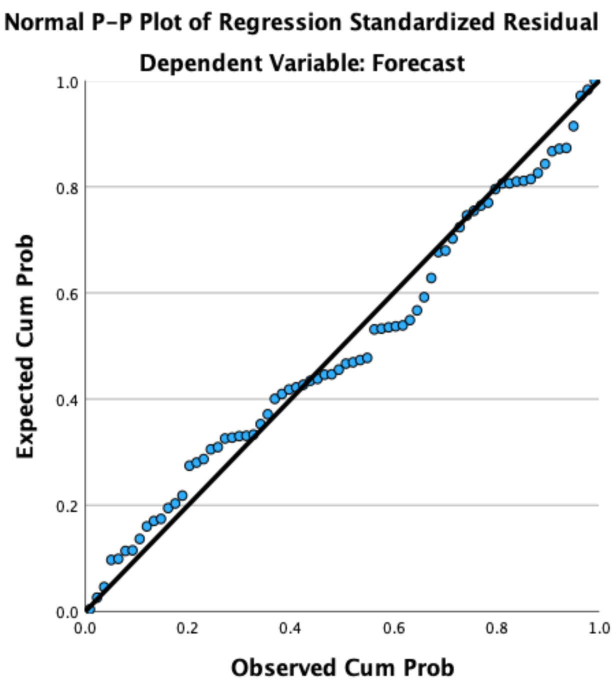


Figure C.3 Plot of standardized residuals, Forecasting Exercise-3

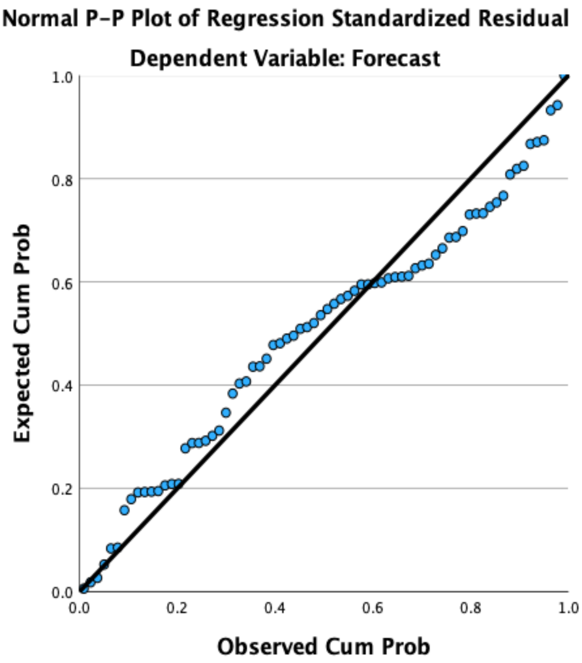
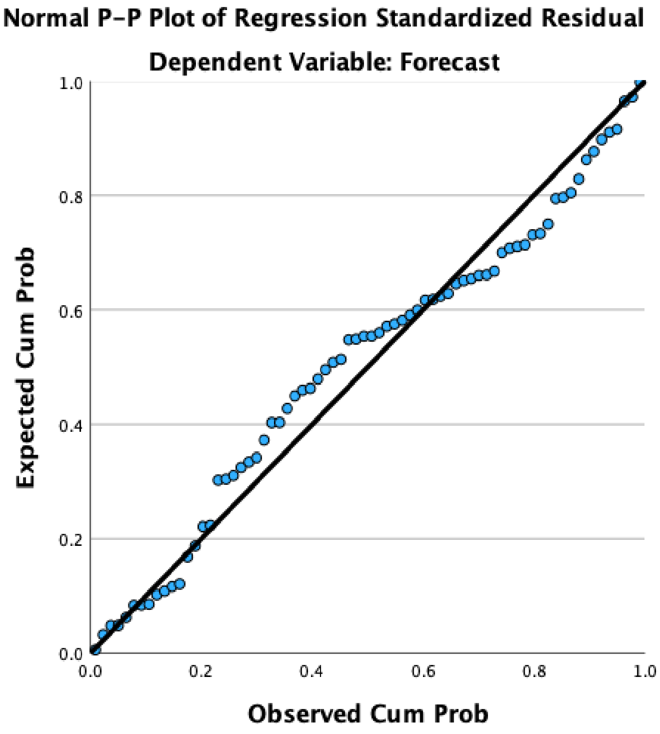


Figure C.4 Plot of standardized residuals, Forecasting Exercise-4



2.2 Homoscedasticity

Table C.5 Breusch-Pagan test for heteroskedasticity, Forecasting Exercise-1

OLS, using observations 1-72
Dependent variable: scaled uhat^2

	coefficient	std. error	t-ratio	p-value	
const	−1.92979	1.55997	−1.237	0.2206	
Treatment	−0.634472	0.417557	−1.519	0.1336	
Sex	0.420259	0.415928	1.010	0.3161	
Age	−0.0166149	0.242384	−0.06855	0.9456	
Countryofbirth	−0.0421981	0.500759	−0.08427	0.9331	
Levelofeducation	0.199200	0.289514	0.6880	0.4939	
Employment	−0.0446462	0.452007	−0.09877	0.9216	
EconomicLiteracy	0.0460237	0.0155455	2.961	0.0043	***

Explained sum of squares = 40.5843

Test statistic: LM = 20.292132,
with p-value = P(Chi-square(7) > 20.292132) = 0.004972

Table C.6 Breusch-Pagan test for heteroskedasticity, Forecasting Exercise-2

Breusch-Pagan test for heteroskedasticity
OLS, using observations 1-72
Dependent variable: scaled uhat^2

	coefficient	std. error	t-ratio	p-value
const	1.03359	1.78541	0.5789	0.5647
Treatment	0.615537	0.477900	1.288	0.2024
Sex	0.311077	0.476036	0.6535	0.5158
Age	−0.419686	0.277412	−1.513	0.1352
Countryofbirth	−0.485385	0.573126	−0.8469	0.4002
Levelofeducation	0.0173003	0.331353	0.05221	0.9585
Employment	0.562274	0.517328	1.087	0.2812
EconomicLiteracy	0.00624326	0.0177921	0.3509	0.7268

Explained sum of squares = 22.4813

Test statistic: LM = 11.240666,
with p-value = P(Chi-square(7) > 11.240666) = 0.128460

Table C.7 Breusch-Pagan test for heteroskedasticity, Forecasting Exercise-3

Breusch-Pagan test for heteroskedasticity
OLS, using observations 1-72
Dependent variable: scaled uhat^2

	coefficient	std. error	t-ratio	p-value	
const	1.74354	2.39679	0.7274	0.4696	
Treatment	−0.635364	0.641548	−0.9904	0.3257	
Sex	−0.979962	0.639047	−1.533	0.1301	
Age	0.361509	0.372407	0.9707	0.3353	
Countryofbirth	0.0379054	0.769383	0.04927	0.9609	
Levelofeducation	−0.494605	0.444819	−1.112	0.2703	
Employment	−0.677864	0.694479	−0.9761	0.3327	
EconomicLiteracy	0.0273068	0.0238847	1.143	0.2572	

Explained sum of squares = 53.9395

Test statistic: LM = 26.969751,
with p-value = P(Chi-square(7) > 26.969751) = 0.000337

Table C.8 Breusch-Pagan test for heteroskedasticity, Forecasting Exercise-4

Breusch-Pagan test for heteroskedasticity
OLS, using observations 1-72
Dependent variable: scaled uhat^2

	coefficient	std. error	t-ratio	p-value	
const	2.17727	1.49230	1.459	0.1495	
Treatment	−0.379113	0.399443	−0.9491	0.3461	
Sex	−0.0588627	0.397885	−0.1479	0.8829	
Age	0.266095	0.231869	1.148	0.2554	
Countryofbirth	−0.0991144	0.479036	−0.2069	0.8367	
Levelofeducation	−0.200692	0.276954	−0.7246	0.4713	
Employment	−0.907000	0.432399	−2.098	0.0399	**
EconomicLiteracy	−0.00365389	0.0148712	−0.2457	0.8067	

Explained sum of squares = 16.0098

Test statistic: LM = 8.004892,
with p-value = P(Chi-square(7) > 8.004892) = 0.332163

2.3 Normality of Residuals

Table C.9 Normality tests, Forecasting Exercise-1

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Standardized Residual	0.093	72	0.198	0.969	72	0.072

a. Lilliefors Significance Correction

Table C.10 Normality tests, Forecasting Exercise-2

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Standardized Residual	0.088	72	.200*	0.971	72	0.093

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table C.11 Normality tests, Forecasting Exercise-3

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Standardized Residual	0.097	72	0.093	0.915	72	0.063

a. Lilliefors Significance Correction

Table C.12 Normality tests, Forecasting Exercise-4

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Standardized Residual	0.092	72	.200*	0.978	72	0.253

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

2.4 Multicollinearity

Table C.13 Collinearity Diagnostics

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Treatment	Sex	Age	Country of birth
1	1	1.707	1	0.15	0.15			
	2	0.293	2.414	0.85	0.85			
2	1	2.266	1	0.05	0.07	0.07		
	2	0.534	2.06	0	0.48	0.44		
	3	0.199	3.372	0.95	0.46	0.49		
3	1	3.045	1	0.01	0.03	0.03	0.02	
	2	0.535	2.386	0	0.5	0.42	0	
	3	0.337	3.006	0.03	0.34	0.44	0.22	
	4	0.084	6.027	0.96	0.12	0.11	0.76	
4	1	3.833	1	0.01	0.02	0.02	0.01	0.01
	2	0.536	2.674	0	0.53	0.38	0	0
	3	0.362	3.253	0.01	0.35	0.53	0.1	0.07
	4	0.201	4.364	0	0	0.01	0.39	0.63
	5	0.068	7.525	0.98	0.1	0.06	0.5	0.28
5	1	4.737	1	0	0.01	0.01	0.01	0.01
	2	0.536	2.972	0	0.53	0.36	0	0
	3	0.394	3.469	0	0.33	0.55	0.05	0.02
	4	0.214	4.702	0	0	0.02	0.15	0.72
	5	0.1	6.884	0.07	0.03	0.02	0.74	0.1
	6	0.019	15.949	0.93	0.1	0.04	0.05	0.15
6	1	5.35	1	0	0.01	0.01	0	0.01
	2	0.547	3.126	0	0.15	0.55	0	0.01
	3	0.514	3.226	0	0.59	0.01	0.01	0
	4	0.303	4.204	0	0.13	0.36	0.01	0.26
	5	0.167	5.653	0	0	0.01	0.23	0.48
	6	0.1	7.318	0.07	0.03	0.02	0.7	0.09
	7	0.019	16.949	0.93	0.1	0.04	0.05	0.15
7	1	6.242	1	0	0.01	0.01	0	0
	2	0.548	3.375	0	0.14	0.52	0	0.01
	3	0.514	3.484	0	0.57	0.01	0.01	0
	4	0.331	4.342	0	0.15	0.38	0	0.15
	5	0.172	6.03	0	0	0	0.11	0.66
	6	0.129	6.947	0.01	0.01	0	0.65	0.09
	7	0.052	10.98	0.01	0	0.01	0.2	0.03
	8	0.012	22.828	0.98	0.12	0.08	0.02	0.06

a. Dependent Variable: Forecast

Appendix D – Sample Summary Statistics

Table D.1 Sample and Population Summary Statistics

	Control	Treatment	Population
Sex	0.56	0.51	0.49
Age	2.03	1.94	3 (41.7)
Nationality	0.86	0.85	0.91
Country of birth	0.78	0.76	0.79
Employment	0.58	0.56	0.69
Level of education	3.44	3.33	3.20
Prior inflation expectation	7.96%	8.32%	10.10%
Future inflation expectation	8.52%	8.62%	7.60%

Appendix E – Results

1. Comparing Means and Distributions

1.1 Forecasting Exercise-1

Table E.1 Mann-Whitney U Test

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Forecast is the same across categories of Treatment.	Independent-Samples Mann-Whitney U Test	0.013	Reject the null hypothesis.

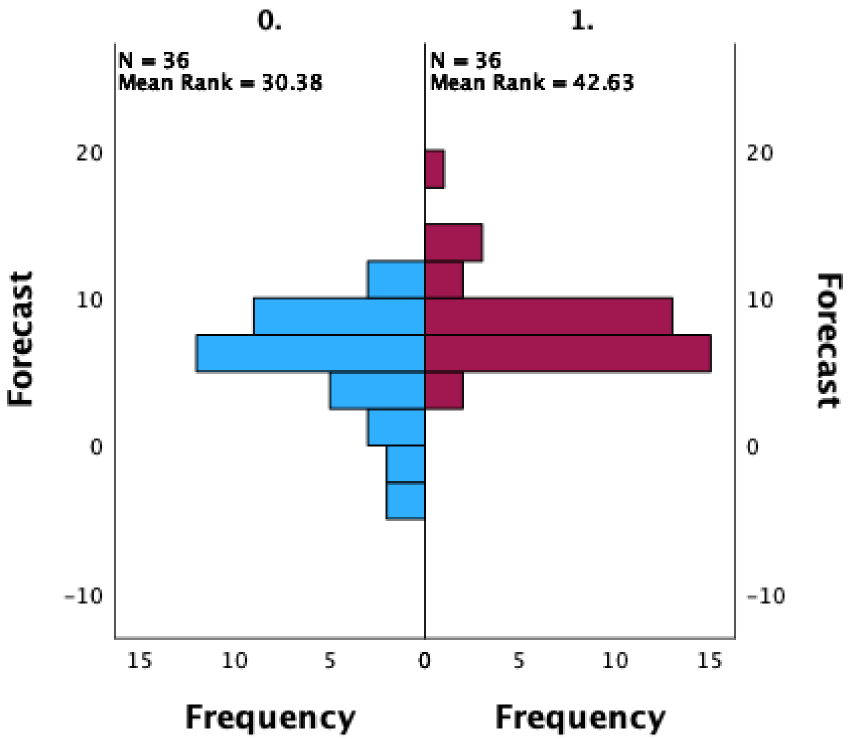
a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Mann-Whitney U Test Summary

Total N	72
Mann-Whitney U	868.500
Wilcoxon W	1534.500
Test Statistic	868.500
Standard Error	88.781
Standardized Test Statistic	2.484
Asymptotic Sig.(2-sided test)	0.013

Figure E.1 Distribution of forecasts the control and treatment groups



1.2 Forecasting Exercise-2

Table E.2 Mann-Whitney U Test

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Forecast is the same across categories of Treatment.	Independent-Samples Mann-Whitney U Test	<.001	Reject the null hypothesis.

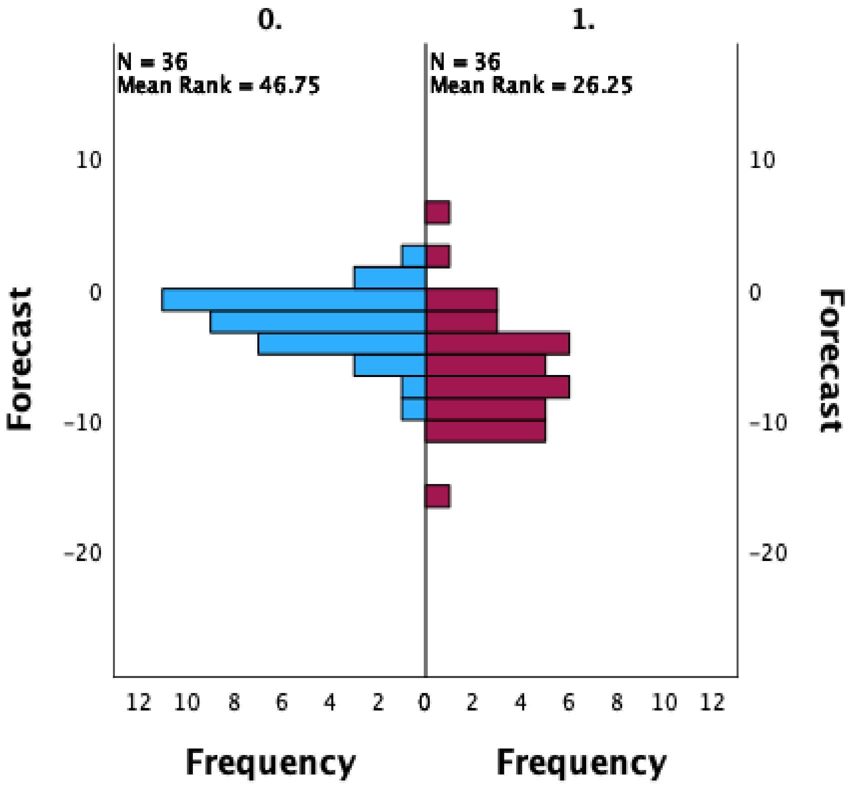
a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Mann-Whitney U Test Summary

Total N	72
Mann-Whitney U	279
Wilcoxon W	945
Test Statistic	279
Standard Error	88.778
Standardized Test Statistic	-4.156
Asymptotic Sig.(2-sided test)	<.001

Figure E.2 Distribution of forecasts for the control and treatment groups



1.3 Forecasting Exercise-3

Table E.3 Mann-Whitney U Test

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Forecast is the same across categories of Treatment.	Independent-Samples Mann-Whitney U Test	0.009	Reject the null hypothesis.

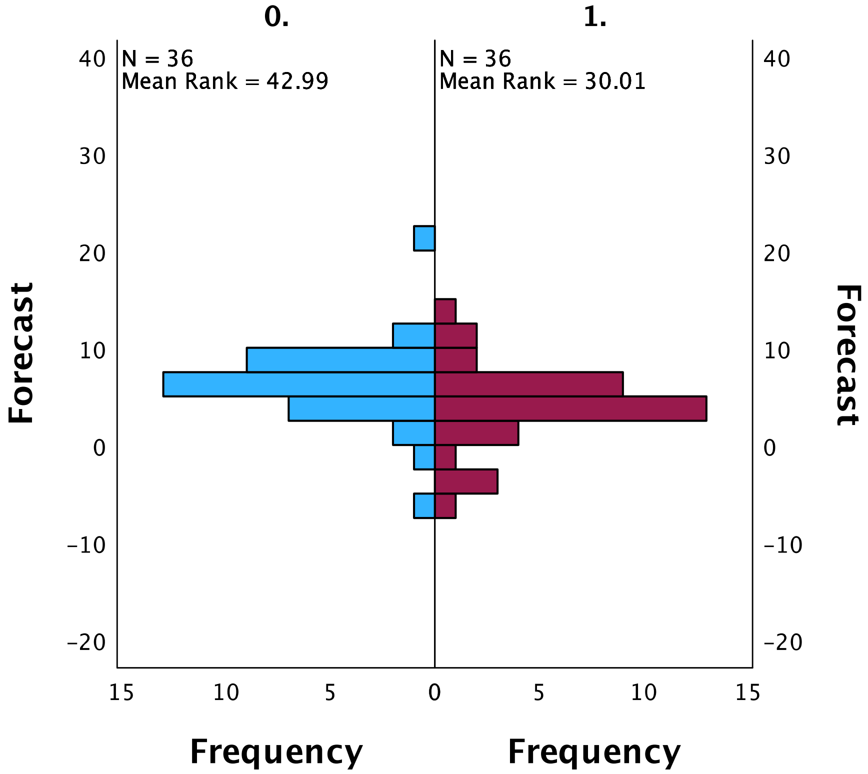
a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Mann-Whitney U Test Summary

Total N	72
Mann-Whitney U	414.5
Wilcoxon W	1080.5
Test Statistic	414.5
Standard Error	88.788
Standardized Test Statistic	-2.63
Asymptotic Sig.(2-sided test)	0.009

Figure E.3 Distribution of forecasts for the control and treatment groups



1.4 Forecasting Exercise-4

Table E.4 Mann-Whitney U Test

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Forecast is the same across categories of Treatment.	Independent-Samples Mann-Whitney U Test	<.001	Reject the null hypothesis.

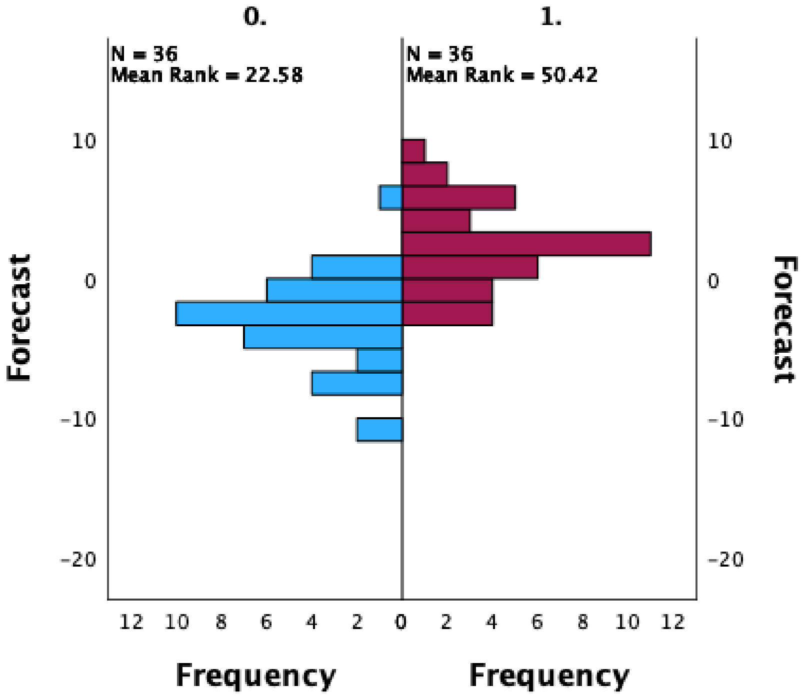
a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Mann-Whitney U Test Summary

Total N	72
Mann-Whitney U	1149
Wilcoxon W	1815
Test Statistic	1149
Standard Error	88.773
Standardized Test Statistic	5.644
Asymptotic Sig.(2-sided test)	<.001

Figure E.4 Distribution of forecasts for the control and treatment groups



2. Variables

Variable Name	Definition	Potential Values
Age	Categorical	18-24, 25-34, 35-44, 45-54, 55-64, 65+
Sex	Categorial	1 if male, 0 if female
Nationality	Categorical	1 if Sweden, 0 if another country
Country of Birth	Categorical	1 if Sweden, 0 if another country
Employment	Categorical	1 if employed, 0 if unemployed
Level of education	Categorical	1-5 each corresponding to a degree, 3 is high school diploma, 4 is bachelors' diploma, 5 is graduate level diploma
Economic Literacy	Percentage	0-100%
Thinking Frequency	How often one thinks about inflation in the last 3 months	0-5
Hearing Frequency	How often one thinks about inflation in the last 3 months	0-5
Learning about inflation	How one typically learns about inflation	1 if media, 0 if other responses
Grocery Habits	Who does the grocery in a household	1 if Myself, 0 If other responses
Prior Inflation Expectations	Inflation expectation for the last 12 months	
Future Inflation Expectations	Inflation expectation for the next 12 months	